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REEXAMINING THE LINK BETWEEN INSTABILITY AND GROWTH IN LATIN AMERICA: A DYNAMIC PANEL DATA ESTIMATION USING K-MEDIAN CLUSTERS*

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We estimate a dynamic panel data model to assess the relationship between different levels of instability—proxied by growth volatility and inflation—and growth in Latin America from 1960 to 2011. Outlying observations could be mistakenly treated as thresholds or regime switch. Hence we use k-median clustering to mitigate the outlier problem and properly identify "scenarios" of instability. Our key findings are that while high inflation is harmful, low inflation is in fact positively related to growth. Volatility is also found to be significant and negative, but with no differential effect—between low and high levels—on growth.

JEL classification: F43, O41, C33

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1. INTRODUCTION

In recent years the detrimental effects of instability on long-term economic growth have increasingly come into focus in the literature. These effects are particularly robust when tested for a sample of emerging economies, where fluctuations in key economic variables are more frequent and intense, with negative and long-term effects on economic growth. In this regard, one crucial aspect is to identify those indicators that accurately capture the kind of instability that characterizes a particular region.

In general, empirical contributions associate instability with the volatility of certain key macroeconomic variables. In a seminal paper, Ramey and Ramey (1995) found a strong empirical negative link between GDP growth rate and the standard deviation to its mean as

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a measure of volatility. More recent empirical literature has developed along the same lines with ambiguous results. Using the same instability proxy, Martin and Rogers (2000) showed that countries and regions with higher standard deviations of growth and unemployment have lower growth rates, but this negative relationship does not hold for non-industrialized countries. In a cross-country study, Hnatkovska and Loayza (2005) found a negative relationship between output growth rate volatility and long-run economic growth. This is particularly clear in countries that are developing, are institutionally underdeveloped, are experiencing the intermediate stages of financial development, or are unable to implement counter-cyclical fiscal policies. They also found that the negative effect of volatility on growth has become considerably larger in the past two decades, and that this is mostly due to deep recessions ("crisis volatility") rather than minor cyclical fluctuations ("normal volatility").

Other empirical contributions highlight statistical issues, compositional effects or a non-linear relationship between instability and growth. For example, Kneller and Young (2001) found that the sign of the estimated coefficient reverses depending on whether volatility is measured over longer or shorter periods. In turn, Tochkov and Tochkov (2009) pointed out that the ambiguous results they found could stem from common shocks across regions that have a different impact on the growth-volatility relationship in different countries. Kose *et al.* (2008, 2006) showed that this relationship has been changing over time and across different country groups in response to increased trade and financial flows. In particular, the evidence suggests that the nature of this relationship differs even among developing countries, depending on their level of integration into the global economy.

Although not as extensively as the GDP-associated volatility measure, inflation has also been used as a proxy for macroeconomic instability[1]. A negative link between inflation and growth was assessed in Kormendi and Meguire (1985), Barro (1991), Fischer (1993), Bruno and Easterly (1998), Sarel (1995) and Ghosh and Phillips (1998). Not surprisingly, Dabús (2000) and Dabús *et al.* (2012) found that in Latin America inflation is essentially harmful to economic performance in the presence

1. Another measure of instability widely used in the literature is the volatility of government expenditure. Two examples are Afonso and Furceri (2010) and Fatás and Mihov (2013), who showed that the volatility of fiscal policy reduces long-term economic growth. Ocampo (2008) emphasized that the different forms of macroeconomic instabilities are not correlated, so both the broad definition and the trade-offs involved deserve more attention.

of high and hyper-inflation. These results are in line with those found by Loayza *et al.* (2003) and Bittencourt (2012).

In turn, Khan and Senhadji (2001) carried out panel data estimations and found a significant and negative effect of inflation only above a certain a “threshold” inflation value, which is higher for developing countries. Also, Judson and Orphanides (1999) found a significant negative inflation-growth effect for a large panel, but only for inflation rates higher than 10%. Using a panel smooth transition model, Ibarra and Trupkin (2011) estimated an inflation-rate threshold for industrialized countries of 4.1%, while for non-industrialized countries the threshold was 19.1%. Similarly, Kremer *et al.* (2013) estimated that inflation rates exceeding 17% are associated with lower economic growth for non-industrialized countries, while below this threshold the correlation is not significant.

Notwithstanding the relevance of the results attained so far, there is still little evidence about the link between instability and growth for Latin American economies, as most of the empirical work on developing economies focuses on Asian countries or uses a sample of emerging economies in general. Following Edwards (2004), the region has some idiosyncratic features that justify a separate analysis: It stands alone in both inflation rate and GDP growth rate volatility, which brings up differences with other developing regions. In fact, Latin America is on average two to three times more volatile than industrialized regions in terms of non-monetary quantities and has been more volatile than any other region of the world except Africa and the Middle East.

In this sense, our goal is to empirically assess the link between instability and growth in Latin America as well as the sign of that link. In particular, we are interested in analyzing whether low- and high-instability scenarios have a statistically different impact in terms of explaining the growth performance of the region. However, our dataset has several outliers, which means that any procedure used to identify regimes (in the Markov-switching sense) or thresholds (as in panel threshold models) will be distorted by the large variance of these observations.

In light of this issue, our contribution is to go beyond the traditional empirical estimation of a growth model á la Barro, by using pre-estimation clustering techniques to identify different instability scenarios that are not contaminated by the presence of aberrant observations.[2] One

2. We would like to emphasize that we use the term “scenarios,” rather than “regimes” or “levels” to make the distinction from other procedures such as Markov switching processes or panel threshold models.

way of dealing with this is to use the k-median clustering algorithm. Its purpose is to partition the data into k-clusters that are less than or equal to the n observations, to minimize the within-cluster sum of squares for every k cluster created. Choosing an appropriate number of clusters allows us to group observations into different categories of low and high instability without considering extreme cases that could indicate a falsely significant relationship between instability and growth.

Our main findings are that the clustering techniques actually help capture the differential performance of economies in the low- and high-instability scenarios. After removing outliers from the sample, the regression outcomes are robust and show that while inflation has a significant and negative effect on economic growth only above an average triannual rate of 57%, our volatility proxy also has a negative and significant impact on growth, but without any differential effect among the various clustering techniques applied to the data.

The structure of the paper is as follows. Section 2 describes the data used and the empirical strategy followed; Section 3 reports our results and Section 4 offers some concluding remarks.

2. Empirical analysis

2.1 Data and summary statistics

We use a sample of 17 Latin American economies and 17 consecutive and non-overlapping three-year periods from 1960 to 2011. The countries in the sample are Argentina, Bolivia, Brazil, Chile, Colombia, Costa Rica, Ecuador, El Salvador, Honduras, Guatemala, Mexico, Nicaragua, Panama, Paraguay, Peru, Uruguay, and Venezuela.

Table 1 summarizes the information about the variables and Table 2 presents the descriptive statistics and Spearman correlations. Following Ramey and Ramey (1995), we begin by calculating the simple correlation of growth and instability. Table 3 shows the country-specific correlations between our variables of interest.

The average correlations between growth, volatility and inflation are small for the complete sample (see Table 2). However, country-specific correlations show high variability across countries. The correlations between economic growth with inflation and growth rate volatility are negative and considerably different from zero in approximately 50% of

Table 1. Variable descriptions and sources

Variable	Description	Source
Growth	Gross domestic product (GDP) per capita growth rate (based on constant 2000 U.S. dollars).	World Development Indicators, World Bank.
Growth volatility	Standard deviation of GDP per capita growth rate.	Authors' calculations based on World Development Indicators, World Bank.
Inflation	Inflation rate of consumer prices (%) in natural logs.	Authors' calculations based on World Development Indicators, World Bank.*
Investment	Gross fixed capital formation/GDP, in natural logs.	World Development Indicators, World Bank.
Merchandise trade	Merchandise trading/GDP, in natural logs.	World Development Indicators, World Bank.

Source: Authors' own elaboration based on World Bank information.
Note: * Inflation rate data for Argentina from 2007 onwards were taken from the web site www.inflacionverdadera.com.

Table 2. Descriptive statistics and correlations

Descriptive statistics	Growth	Growth volatility	Inflation	Investment	Merchandise trade
Mean	1.6277	2.7225	0.1254	1.2672	1.5542
Std. dev.	2.9922	2.2923	0.2642	0.0960	0.1728
Min.	-12.5023	0.1379	-0.0056	0.9884	1.0136
Max.	9.5214	15.2251	1.8800	1.5050	1.8730
Correlations	**Growth**	**Growth volatility**	**Inflation**	**Investment**	**Merchandise trade**
Growth	1				
Growth volatility	-0.2557	1			
Inflation	-0.2023	0.237	1		
Investment	0.0792	0.1613	0.1167	1	
Merchandise trade	-0.1765	0.0904	0.2884	0.1552	1

Source: Authors' calculations based on the data described in Table 1.

cases (see Table 3). Thus, until now the evidence has suggested a negative instability-economic growth association in Latin American countries.

Table 3. Country-specific correlations

Correlations	Growth/volatility	Growth/inflation	Volatility/inflation
Argentina	-0.0824	-0.5222	0.3830
Bolivia	-0.3593	-0.6127	-0.0204
Brazil	-0.0181	0.2010	-0.0883
Chile	-0.6345	-0.3724	0.5040
Colombia	-0.4143	-0.2170	0.0279
Costa Rica	-0.7278	-0.3752	0.0625
Ecuador	0.0050	-0.3794	0.2831
El Salvador	-0.5990	-0.2577	0.2511
Guatemala	0.1074	-0.1476	-0.0931
Honduras	-0.1188	-0.1191	0.2732
Mexico	-0.6340	-0.3410	0.2616
Nicaragua	-0.6860	-0.3353	0.5848
Panama	-0.4711	0.1343	0.0397
Paraguay	-0.1645	0.0799	-0.1683
Peru	-0.6310	-0.6985	0.6450
Uruguay	-0.4345	-0.0112	0.1891
Venezuela	-0.2915	-0.1455	0.1793

Source: Authors' calculations based on the data described in Table 1.

In the following subsection we control for extreme values of the explanatory variables of interest by grouping observations into different clusters and then estimating different models that incorporate a set of control variables and country- and time-specific effects.

2.2 Clustering

Aberrant observations in the panel data set could bias the estimation results, because classical estimators (such as OLS, GLS, 2SLS and GMM) have low breakdown points.[3] Moreover, they can also invalidate the results of non-linear estimations. Outliers may be mistakenly

3. The breakdown point of an estimator is defined as the highest fraction of outliers that an estimator can withstand; it is one of the most popular measures of robustness (Donoho and Huber, 1983; Rousseeuw and Leroy, 1987).

treated as another regime when in fact they are not, thus leading to spurious regression results.[4]

Nonetheless, no formal techniques have been developed so far to detect outliers in panel data frameworks. Therefore we follow the standard practice and use the trimmed mean as a rule of thumb. At first glance, the data indicate that the instability proxies have at least one outlying observation. Table 2 shows that the maximum or minimum values of the variables fall out of the range of the trimmed mean. Because of Latin America's history of instability, our data set could include more outliers, so we partition the inflation and GDP growth-rate volatility data into groups using the k-median clustering method (Jain and Dubes, 1981). This algorithm is a variation of k-means clustering (Hartigan, 1975) where instead of calculating the mean for each cluster to determine its centroid, it calculates the median—which is not affected by extreme values—to minimize error over all clusters with respect to the 1-norm distance metric, as opposed to the square of the 2-norm distance metric used by the k-means algorithm. If there are aberrant observations in the data, they should form groups by themselves. These clusters will not have enough observations and therefore will not be used in the panel data estimations.

The k-median algorithm can be written as:

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

where μ represents the median of each cluster. The inner sum represents the sum of squares of the difference between observation x in cluster s and the median of cluster s. The outer sum indicates that the sums of all clusters from i to k are totaled to get a single number that will be minimized.

The algorithm is composed of the following steps:

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

4. Knez and Ready (1997) find that the "size effect"—that is, that smaller companies perform better—detected by Fama and French (1988) disappears if outliers are removed from the sample. Similarly, Zhou *et al.* (2004) refute the work of Levine and Zervos (1998) by taking the outliers' effect into account. The authors find that stock market liquidity no longer has any statistically significant effect on GDP growth.

2) Assign each object to the group that has the closest centroid. In our work, we have chosen to work with the Euclidean distance.

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

4) Repeat steps 2 and 3 until the centroids no longer move. This produces a separation of the objects into groups from which the metric to be minimized can be calculated.

Unfortunately, there is no general theoretical solution to determine the optimal number of clusters for any given data set. A simple approach is to compare the results of multiple runs with different k classes and choose the one that best fits a given criterion. In our case, we tested the number of clusters with the Calinski-Harabasz (1974) pseudo F-index (see appendix).

Figures 1 and 2 show the GDP per capita growth rate plotted against the resulting clusters of growth volatility and inflation. Each triannual observation is represented by one dot.

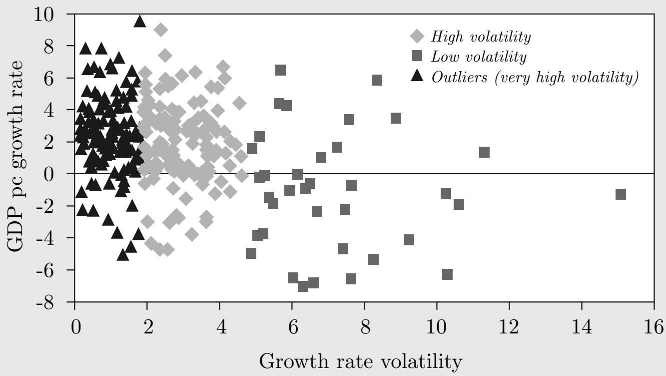
These figures reflect both of the uses we make of the cluster approach. From the distribution of the observations in the plot, it becomes quite clear that if we run a simple regression between GDP growth rate and the interest variable (volatility or inflation), a significant and negative relationship is likely to be found. However, as there are several outliers in the dataset, the result would be spurious since it would be driven by a few events. In this sense, the cluster approach is crucial to identifying aberrant observations.

The second issue is in regard to the remaining observations: If they can form distinct clusters (of low and high levels of the variables), these clusters may have a differential impact on economic growth.

Figure 1 does not clarify this matter, since the low and high volatility clusters look similar. However, there are indeed some differences between both groups: The high volatility cluster has three times the mean of the low volatility cluster, and also a wider range (see Table 10 with this descriptive statistics in the appendix).

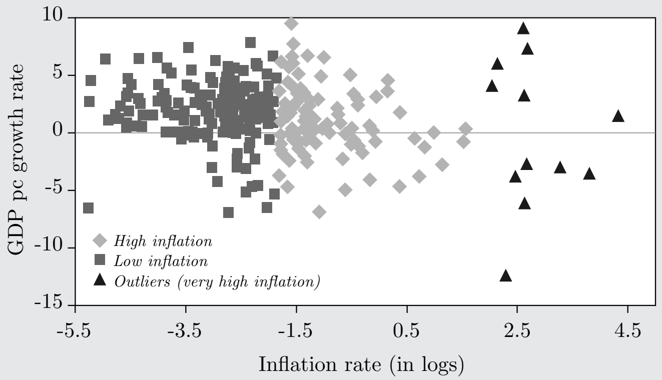
Figure 2 has fewer outliers and more distinct clusters of low and high inflation. At first glance, low inflation seems to be related to positive growth rates, while high inflation might be negatively related to growth.

Figure 1. Growth rate volatility and GDP per capita growth rate, by cluster



Source: Authors' calculations.

Figure 2. Inflation rate and GDP per capita growth rate, by cluster



Source: Authors' calculations.

2.3 Econometric methodology

Following Loayza *et al.* (2003), we estimate a dynamic endogenous growth specification of the form:

$$y_{i,t} - y_{i,t-1} = \alpha y_{i,t-1} + \beta X_{i,t} + \beta' Z_{i,t} + \eta_i + \lambda_t + \psi_{i,t} \tag{2}$$

where $y_{i,t}$ is the natural logarithm of output per capita for country i at time t (triannual averages), and $y_{i,t} - y_{i,t-1}$ is the growth rate of output per capita. $X_{i,t}$ and $Z_{i,t}$ are the vectors of explanatory variables.. The first one includes the instability measures, and the second one includes two control variables: gross investment as a share of GDP and the exports plus imports ratio to GDP[5]. The residual has three components: an unobserved country-specific effect, η_i; an unobserved time-specific effect, λ_t; and an independent and identically distributed error term, $\psi_{i,t}$.

A lagged dependent variable is included, which makes the regression become dynamic in nature. Consequently, we use the system GMM estimator developed by Arellano and Bover (1995) and Blundell and Bond (1998). This estimator combines the first-differenced GMM approach—which uses lagged independent variables as instruments in the levels equations to deal with possible endogeneity issues in the regressors—with the original equations in levels, thus increasing the efficiency of the estimators when the series are very persistent. Therefore, their lagged levels are only weakly correlated with subsequent first-differences (Blundell and Bond, 1998). The estimation of growth models using the system-GMM estimator for linear panel data was introduced by Levine *et al.* (2000) and has now become common practice in the literature (see Durlauf, *et al.*, 2005, and Beck, 2008).

5. These variables have been found to be robust in various estimations of economic growth for Latin American economies (Loayza *et al.*, 2003, Ramírez Rondán, 2007, Dabús *et al.* 2012). We do not include educational variables (captured by proxies such as school attendance, enrollment, and years of schooling, among others) because several studies have found that they are not significant for economic growth when testing a sample of emerging economies. In this regard, Loayza, Fajnzylberg and Calderón (2005) explain that the lack of significance of the educational variable in some of their specifications should serve as a caution about the pitfalls of educational measures as proxies for human capital. The same result is found in Dabús and Laumann (2006). The authors explain that it may be that in these countries, human capital accumulation is not effective in fostering growth because they lack the social and economic context to benefit from a more educated population.

We use a sample of 17 Latin American economies and 17 consecutive, non-overlapping three-year periods from 1960 to 2011. The proxies for economic instability, i.e., inflation rate and GDP growth rate volatility, are treated as exogenous variables.[6] The other explanatory variables can be affected by economic growth so they are treated as endogenous.

To avoid biased estimators resulting from "too many instruments," we follow Roodman's (2009) approach. 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, because the small panel sample size may produce a downward bias of the estimated asymptotic standard errors, we implement Windmeijer's correction procedure (Windmeijer, 2005).

5. Regression results

This section presents the estimations of Equation (2). In Table 4, which contains system-GMM estimates, column 1 shows the results of the estimation using the whole sample and columns 2 through 5 show the results of the estimation of the model when the instability proxies are grouped into two clusters of data, representing low and high levels of inflation and growth volatility, respectively.

To maintain a low number of instruments, we carry out the regressions by collapsing the corresponding variables. All the regressions pass the second-order serial correlation test. The null hypothesis that the error term is not serially correlated cannot be rejected. Most p-values for the Hansen test satisfy the conventional significance levels with an average value of 0.747. The p-values for the difference-in-Hansen tests for the validity of the instruments are also acceptable. The validity of the subsets of instruments is established for almost all regressions.

6. We assume perfect exogeneity for growth volatility because treating it as predetermined—i.e., using lagged values of the variable as instruments in the GMM estimation—generates serious correlation problems and very low p-values of the Sargan tests. This happens because volatility is quite persistent and thus a high number of lags are needed to avoid the endogeneity bias in a growth regression, which would lead to the "too many instruments" problem (Roodman, 2009).

Since Ramey and Ramey (1995), it has been generally accepted that output volatility is detrimental to economic growth. Thus, assuming perfect exogeneity allows us to avoid any endogeneity issues without the need to consider the reverse causality (from growth to volatility).

Table 4. GMM – complete sample and clustered data

Variables	(1) System GMM	(2) Low inflation	(3) High inflation	(4) Low growth volatility	(5) High growth volatility
Lagged GDP growth rate	0.217	0.199	-0.106	0.0258	0.288**
	(0.245)	(0.260)	(0.397)	(0.867)	(0.029)
Growth volatility	-1.334***	-0.807***	-0.819**	-0.744***	-1.020***
	(0.000)	(0.000)	(0.021)	(0.002)	(0.001)
Inflation	0.471	0.794**	-0.551*	0.527	-0.0328
	(0.104)	(0.044)	(0.074)	(0.216)	(0.875)
Investment	8.983	7.262	13.89**	11.48	4.440
	(0.107)	(0.372)	(0.016)	(0.106)	(0.561)
Merchandise trade	-5.728***	-6.436***	-4.982**	-5.574**	-4.625
	(0.003)	(0.000)	(0.016)	(0.011)	(0.261)
Constant	3.492	6.639	-6.532	-1.309	5.822
	(0.639)	(0.482)	(0.333)	(0.855)	(0.373)
Observations	257	154	92	111	113
Number of groups	17	17	15	17	17
Number of instruments	22	22	22	22	22
AR1 test (p-value)	0.003	0.038	0.102	0.153	0.052
AR2 test (p-value)	0.641	0.746	0.365	0.354	0.301
Hansen test (p-value)	0.548	0.692	0.875	0.557	0.638

Source: Authors' estimations based on the data described in Table 1.
Note: Robust p-value in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

In line with Ramey and Ramey (1995) and Martin and Rogers (2000), our results in estimations (1) through (5) show a negative relationship between growth rate volatility and economic growth. This result is robust to all specifications of the model. In turn, inflation is not significant for the total sample. Nevertheless, this variable becomes relevant when we group observations into low- and high-inflation clusters and cut off aberrant observations (e.g., hyperinflation episodes). Although we do not control for non-linearity between inflation and growth, our results partially match those of Kremer *et al.* (2013): we observe that low levels of inflation may be growth-enhancing while very high inflation scenarios are clearly detrimental.

In relation to the control variables, the investment-to-GDP ratio is significant and positive at high inflation. As pointed out by Cheung *et al.* (2012), the conventional assumption about aggregate production functions is that marginal return on investment declines and at some point becomes negative as the capital-output ratio increases. However, there are reasons to doubt that returns will be zero or negative in an international context where capital flows freely, investment is not only driven by profit considerations, the institutional framework is not stable and financial markets are incomplete, a situation that occurs most frequently in less developed countries.

In fact, Cheung *et al.* (2012) also pointed out that if non-profit-driven capital flows are quantitatively important, the observed link between investment and growth could be weakened. This result is more probable when countries are in the intermediate stages of financial development and the financial system is unable to guarantee assignment of savings flows to productive investment opportunities. Moreover, high inflation disrupts the operation of financial markets, causes uncertainty about relative prices, increases the risk associated with investment and reduces the expected return. Therefore, it is possible to assume that while a non-significant relationship prevails in low/moderate inflation scenarios, a positive and significant coefficient is the norm in a developing economy with high inflation: that is, the lower the output per capita growth, the lower the rate of investment.

The resulting trade coefficients are highly significant but show a negative relationship with growth rate. This result requires explanation since conventional trade theory would predict a positive link. Even before Rodriguez and Rodrik (2001) criticized the robustness of econometric tests of the openness-to-growth causality, scholars became interested in observing certain nonlinearities in the relationship (Miller and Upadhyay, 2000) and understanding the channels through which openness may affect the growth rate (Matsuyama, 1992; Coe and Helpman, 1995; Basu and Weil, 1998). Following Andersen and Babula (2008), openness gives access to foreign inputs and technologies, expands market size and facilitates diffusion of knowledge. However, a minimum level of human capital for adapting techniques is required, or a sufficient stock of general knowledge to change the patterns of specialization after the opening. In developing countries where these requirements are not met, the theoretical literature predicts a probable highly negative relationship between trade and growth, which is what we found for the entire sample of Latin American countries.

Table 5 reports the estimation results using two other variable groupings: the World Bank income-level classification and the geographical location of the countries. The former indicates that the Latin American countries in this study belong either to the upper-middle or low-middle income level. The geographical criterion divides the sample into South and Central American countries.[7] Our new results on volatility corroborate the conclusions reached in our study, namely, that there is a negative relationship between volatility and growth. Nevertheless, the other explanatory variables become non-significant when the data are grouped according to income and geographical criteria.

Table 5. GMM – Data grouped by income level and geographic region

Variables	(6) Low-medium income	(7) High-medium income	(8) Central region	(9) South region
Lagged GDP growth rate	0.368**	-0.0804	0.158	0.0762
	(0.022)	(0.520)	(0.430)	(0.675)
GDP growth rate volatility	-0.766**	-1.344***	-0.982**	-1.251***
	(0.023)	(0.003)	(0.010)	(0.001)
Inflation in logs	-0.286	-0.0713	-0.0136	0.0442
	(0.391)	(0.802)	(0.979)	(0.880)
Investment in logs	1.489	0.559	8.547	2.089
	(0.725)	(0.943)	(0.266)	(0.874)
Merchandise trade	-1.044	-2.043	-2.812	-2.939
	(0.472)	(0.552)	(0.241)	(0.430)
Constant	1.487	8.607	-2.882	7.322
	(0.845)	(0.390)	(0.781)	(0.605)
Observations	105	152	102	155
Number of groups	7	10	7	10
Number of instruments	22	22	22	22
AR1 test (p-value)	0.042	0.006	0.033	0.014
AR2 test (p-value)	0.333	0.613	0.488	0.680
Hansen test (p-value)	0.989	0.997	1.000	0.941

Source: Authors' estimations based on the data described in Table 1.
Note: Robust p-value in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

7. We had estimated the same models with the incorporation of three different variables that capture the effects of political stability (polity2) and authoritarian (autoc) and democratic (democ) regimes. To do this, we used Polity IV database version 12. These variables are constructed as indexes derived from codings of competitiveness of political participation, constraints on the exercise of power by the executive, and civil liberty guarantees, among other factors considered. None of these variables were found to be significant at a 95% confidence level. They did not significantly alter the major results of our work: growth volatility and inflation were robust in all these specifications. The regressions that include the political variables are available from the authors upon request.

6. Concluding remarks

In this paper we reexamine the relationship between instability and economic growth in Latin America over the last 50 years by means of a dynamic panel data model. Economic instability is approximated by the inflation rate and the volatility of the growth rate. In order to address the presence of aberrant observations and identify different instability “scenarios,” we use the k-median clustering algorithm to partition the data into three clusters. The outliers were grouped into one cluster while the rest of the observations were grouped into two other clusters of low and high levels of inflation and GDP rate volatility, respectively.

Our findings show that the different instability scenarios are relevant to explaining economic growth. Indeed, inflation is found to be not significant for the whole sample. However, it becomes significant and positive at low levels and harmful to economic growth at high inflation. On the other hand, growth-rate volatility has a negative and significant impact on growth regardless of the scenario considered and this result is robust to all specifications. This means that while inflation becomes harmful at high levels, volatility is always detrimental to growth. Our evidence suggests that instability can explain most of the economic performance in Latin America in the period studied.

In order to avoid high instability in prices, but most importantly in output, economic policy recommendations should aim for countercyclical aggregate demand policies. However, as in other emerging regions, Latin America not only needs to smooth the normal business cycle, but also needs to reduce the width and frequency of high instability episodes. In turn, as the domestic market is quite restricted, policies should be oriented to facilitating the region’s insertion into new and larger markets that would help expand domestic production.

The region has experienced a dramatic improvement in economic performance over the last decade. The reversal in terms of trade and a large increase in demand for Latin American primary goods exports—especially from China—among other factors, have created very favorable conditions for these emerging economies. However, Latin America has little historical experience in dealing with “abundance” scenarios and certain advantages may become problematic. On the one hand, favorable terms of trade carry the risk of currency appreciation and, in the long run, could provide fewer incentives for innovation activities and technology-based industries; on the other hand, the dualities and structural inequalities of the region could be deepened if inflationary pressures intensify as a result of increasing prices of primary—and necessary—goods. As Fanelli (2008) points out, Latin American countries should design appropriate institutions to manage distribution conflicts, which are the root of most economic collapses in the region: when they occur, there is little (or no) room for countercyclical policies. Although distribution conflicts are not often studied in the context of volatility causes or consequences, the subject merits future research.

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APPENDIX

Choice of clustering method

We chose to work with the k-median clustering method because it is superior to hierarchical methods, as it is less affected by outliers in the sample. This is because the procedure minimizes within-cluster variation and therefore does not rely on a distance measure as hierarchical methods do. For example, if single linkage is used, because it is based on minimum distances it will tend to form one large cluster, with the other clusters containing only one or a few observations each. This is called the "chaining effect." Conversely, the complete linkage method is strongly affected by outliers, as it is based on maximum distances. Clusters produced by this method are likely to be compact and tight. Similarly, the average linkage and centroid algorithms tend to produce clusters with rather low within-cluster variance and similar sizes.

Optimal number of clusters

We use the Calinski and Harabasz (1974) pseudo-F index to determine the optimal number of clusters. Larger values of the index indicate more distinct clustering. We use the Calinski-Harabasz (CH) criterion because various simulation studies (Milligan and Cooper, 1985; Hardy, 1996; Chiang and Mirkin, 2009) find that this criterion most frequently provided the correct number of groups. However, this method takes the form of an ANOVA F-statistic for testing the presence of distinct factors (groups); a critical condition is that the groups have to be approximately of equal sie, or at least contain a sufficient number of observations (at least 5% of the observations in the sample).

Keeping this condition in mind, if we follow the Calinski-Harabasz criterion for the inflation rate, we should choose "two" as the optimal number of clusters. Table 6 presents the resulting index for different numbers of clusters using the k-median clustering algorithm.

Table A1. Different clustering for inflation rate data

Number of clusters	Calinski-Harabasz pseudo-F index
2	324.71
3	162.92
4	109.52
5	81.88
6	65.27
7	71.89
8	55.52

Source: Authors' calculations.

However, the resulting clusters have very different sizes, which could invalidate the efficiency of the C-H criterion. Besides, these two clusters cannot be classified in any economically significant way: the "low inflation" cluster includes observations ranging from a triannual inflation rate of -1.29 to 480.4%, as shown in Table 7.

Table A2. Descriptive statistics of inflation rate clusters – two clusters

Cluster	Obs.	Mean	Std. dev.	Min	Max
1	272	24.557	54.06111	-1.293158	480.424
2	12	2111.953	1970.208	762.7233	7486.894

Source: Authors' calculations.

If we generate three clusters, we obtain the second highest C-H index; again, we obtain the "extreme values" cluster (a third one) and the rest of the observations are grouped into two clusters that are more satisfying in terms of the phenomenon we describe.

Table A3. Descriptive statistics of inflation rate clusters – three clusters

Cluster	Obs.	Mean	Std. dev.	Min.	Max.
1	176	6.426299	4.052284	-1.293158	15.73686
2	96	57.79661	81.12558	16.54102	480.424
3	12	2111.953	1970.208	762.7233	7486.894

Source: Authors' calculations.

Observations grouped in cluster 3 can be identified as “extreme values” while clusters 1 and 2 can be associated with low and high inflation scenarios. Additionally, these two clusters have enough observations to conduct the GMM estimations, so we only discard the observations in cluster 1.

For growth volatility data, the Calinski-Harabasz index returns an optimal number of three clusters. In this case, we follow the index because the clusters formed are similar in size and are economically relevant for the purpose of our work.

Table A4. Different clustering for growth volatility data

Number of clusters	Calinski-Harabasz pseudo-F index
2	280.46
3	507.69
4	435.96
5	426.18

Source: Authors’ calculations.

In this case, cluster 1 groups “extreme values” of the GDP volatility variable, while clusters 2 and 3 could be associated with “high” and “low” volatility scenarios.

Table A5. Descriptive statistics of GDP volatility clusters

Cluster	Obs.	Mean	Std. dev.	Min.	Max.
1	37	7.434157	2.548563	4.936426	15.22508
2	127	2.996534	.7352036	1.946945	4.675031
3	125	1.049503	.4972255	.1379393	1.906352

Source: Authors’ calculations.