Designing a contemporaneity index: Detecting regional similarities in South America, 1961–2018

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This study present an operational characterization of contemporaneity among variables based on the transformation of their corresponding time series into symbolic ones by applying either a Markov switching approach or the symbolic aggregate approximation method. Then, the authors extract vectors from the resulting symbolic time series, characterizing the pattern of change or permanence in time. The scalar product between the vectors corresponding to two variables yields the index of contemporaneity between them. The study apply this method to detect a ranking of synchronic patterns of evolution of gross domestic product (GDP) and investment between several South American economies.

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Introduction

Economic regions are defined not only in terms of geographic proximity but also by either the similarities or complementarities among their components. While these are sometimes readily evident for policymakers, other relations can be harder to detect, hiding possible opportunities for integration. Here, we seek to design a procedure for the detection of the presence of a particular type of relation among economic variables, which we call *contemporaneity*, characterized by the synchronic variation of their values. The existence of contemporaneity or its radical absence may indicate a strong opportunity for creating new associations in regional contexts aimed at either getting stronger together or generating joint hedging or compensatory mechanisms.

Since variables can be associated in terms of their patterns of temporal behavior, statistics has characterized several forms that such relations can adopt, yielding notions such as correlation, causation and simultaneous determination (Hamilton

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1994, Wooldridge 2002). On the other hand, the problem of characterizing different forms of temporal clustering has given rise to several new branches of statistical analysis (see, for example, Deng et al. 2013, Wu et al. 2015 for general examples). Nevertheless, the contemporaneity of variables, an intuitive concept, has not been considered until recently (Delbianco–Fioriti 2017), and it still requires a more developed formal expression (see Aghabozorgi 2015 for a related review of time series clustering). This step should amount to a more abstract conception of this notion, since in practice, the concept of similarity based on contemporaneity or synchronization is independent of the methodology employed to detect it.

The goal of this paper is to contribute to the high-level characterization of the concept by providing an *operational* specification of the contemporaneity of variables based on the construction of *symbolic time series* (Brida 2006, Brida–Garrido 2006, Brida et al. 2009). More precisely, our characterization starts by translating the original time series into vectors with entries drawn from a small set of symbols. By defining these symbols adequately, we can develop a very simple algebraic framework that allows us to assign a contemporaneity index to any pair of time series. The key idea behind this procedure is that the use of symbolic series as an input allows us to dismiss concerns about the actual data generation processes and to focus only on the synchronic movement of the series.

The main impact of our work can be assessed in its application to regional analysis, allowing the extension of the usual narrowly conceived concept of "region", based on the idea that the countries that compose it behave in a similar way, especially when they share historical or cultural roots. In fact, this is the common assumption behind the analyses that take Latin America (or at least South America) as a single world region. Several analyses using more standard temporal clustering methods show that this idea may be correct (see Gonzalez–Delbianco 2021, Delbianco et al. 2021 for specific economic examples in Latin American contexts). It is extremely important and useful to use the spatial and geographical dimensions to generate new indices and models that allow the generation of new knowledge and insights. See Akbash et al. (2018), Delbianco et al. (2019) and Varga et al. (2016) for practical illustrations of such cases.

An empirical hypothesis that we can state to support the introduction of the notion of contemporaneity is that the presence of strong correlations does not necessarily imply the strict association of behaviors over time. Worse yet, strong correlations may hide the lack of simultaneity of abrupt changes in the time series caused by relevant events. The same is true for other methods of analysis that yield measures of association between time series.

Contemporaneity, in turn, despite its simplicity, facilitates the detection of behaviors disproving wrong claims about the close association of economic variables in a region, revealing instead that nonneighboring countries may be closer in their association. This opens the door to the possibility of redefining the meaning of "region", allowing for finer distinctions about the degree to which behaviors are associated.

As stated, our point of departure is the translation of the original time series into a *symbolic time series*. A potential limitation of applying the standard Symbolic Time Series Analysis is that the range of symbols can be arbitrarily chosen, leading to potentially different specifications of contemporaneity. To limit that possibility, we consider two structural approaches to finding a set of symbols translating the numerical values of the time series.

One alternative is to apply a Markov switching analysis (Hamilton 1994, Delbianco et al. 2022). This involves conceiving each time series as generated by an underlying Markov process with a small number of states or *regimes*. This allows us to replace every numerical value in an original time series with the symbol of the dominant regime at the corresponding time period.

The second alternative is resorting to *Symbolic Aggregate approXimation* (Lin et al. 2003). This approach takes the averages of the numerical values of the series at regular time windows and translates them into a small set of symbols. This is closely related to smoothing out the series and transforming them into a stepwise series of symbols.

Either way, the symbolic series can be represented as vectors in which the components indicate whether, from a given period to the next, the symbols change or remain the same, represented by either –1 or 1. Then, given two variables, we take the corresponding vectors (of the same dimensionality) and find their scalar product, which yields the index of contemporaneity between those two variables. A higher value indicates a higher degree of contemporaneity among the variables, while a large negative value shows an out-of-step evolution.

We use this proposed methodology to analyze the evolution of a specific group of countries that a priori share a common geographical context and a similar history, namely, the South American countries. We show that even when the correlations between economic variables have been extensively studied in the region (Thorp 1998), when we consider the specific timing of regime changes, they fail to be synchronized between countries and time periods. The presence of this significant difference between a strong correlation among time series but with a disconnection between breaks poses important questions about the conception of South America as a single region. This also has practical policy implications that go beyond our analysis.

The remainder of this paper is structured as follows: briefly presentation the technical details of symbolic time series analysis, SAX and Markov switching analysis, the description of the index of contemporaneity, an example of application, namely, to the detection of contemporaneity among growth rates in South America and establishing a ranking of "closeness" among economies in terms of the behavior of their GDPs, conclusions.

Symbolic time series

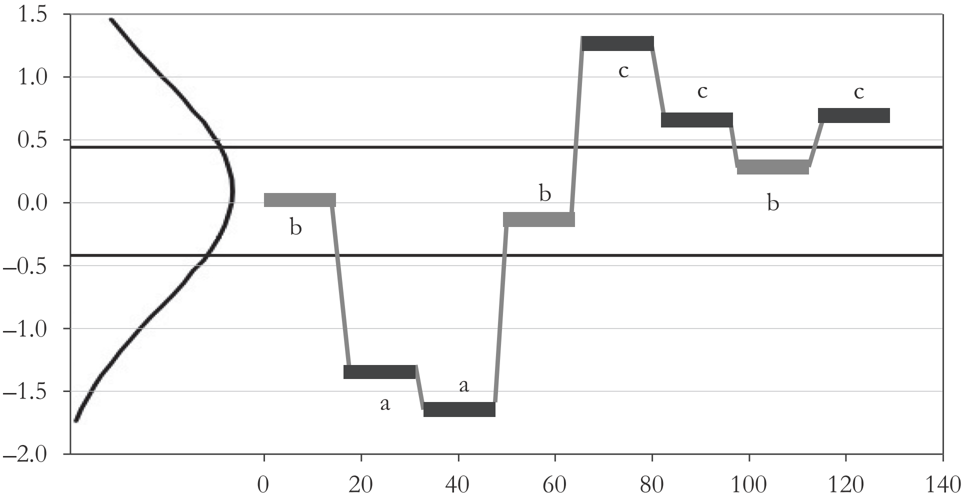
Symbolic time series analysis (STSA) is based on the idea that numerical data generated by a dynamical system can be translated into a symbolic representation without making any assumption about the specific details of the underlying system. The idea is that the essential properties of the generating system can be recovered by choosing an appropriate symbolic coding.

STSA has been useful to study business cycles, seeking to detect the breakpoints that can be relevant to understanding the behavior of the underlying systems (Brida–Punzo 2003, Brida 2006, Brida et al. 2009). STSA has also been applied to analyze economic growth, comparing different evolution paths (Brida–Punzo 2003).

Figure 1, adapted from Lin et al. (2003), shows an original series and its translation into a symbolic series. The values below –0.5 are assigned symbol **a**, those between –0.5 and 0.5 are labeled **b**, and those above 0.5 are identified with letter **c**. We can see that this is just one possible way of translating the series into a symbolic one.

Figure 1

Illustration of symbolic regimes



Source: Lin et al. (2003).

In the next subsections, we discuss two different systematic ways of assigning symbols to ranges of values in numerical time series.

Symbolic aggregate approximation

Lin et al.'s (2003) approach to STSA, Symbolic Aggregate ApproXimation (SAX), consists of reducing the dimensionality of a time series in two steps. The first step is Piecewise Aggregate Approximation (PPA), which replaces the original series with a sequence of segments corresponding to the average of the values in a time bin, specified arbitrarily. The second step in the procedure consists of translating the PPA series into a discrete string of symbols drawn from a given dictionary.

Formally:

– **PPA step**: a time series $C = \{c_j\}_{j=1}^{n}$ of length n is represented by a vector $C^{-} = (c^{-}_1, \dots, c^{-}_w)$ in a w-dimensional space.

The ith element of C^{-} is calculated as:

$$c^{-}_i = \frac{w}{n} \sum_{j=\frac{n}{w}(i-1)+1}^{\frac{n}{w}i} c_j$$

– **Symbolization step**: An alphabet size is defined as an arbitrary integer $d > 2$. The PPA time series is normalized, and a sorted list of *breakpoints* $B = \beta_1, \dots, \beta_{|d|-1}$ is defined such that the area under a $N(0,1)$ Gaussian curve from β_i to β_{i+1} is $\frac{1}{|d|}$. Once a list of symbols $\{\alpha_i\}_{i=1}^{d}$ is defined, the PAA approximation C^{-} is translated into a *word* $\hat{C} = \hat{c}_1, \dots, \hat{c}_w$, where $\hat{c}_i = \alpha_j$, iff $\beta_{j-1} \leq c^{-}_i < \beta_j$.

The PPA step divides the total period into shorter „bins". Given any bin, the procedure takes the average of the numerical values of the series in that bin. Then, a new series is generated by replacing each observation in a bin with the corresponding average value.

The symbolization step is more involved but can be illustrated in Figure 1. If we want to use three symbols (e.g., **a**, **b** and **c**), we take the series obtained at the PPA step and impose a normal distribution with mean 0 and variance 1 on the range of values of the series. Then, we detect the breakpoints that divide the area under $N(0,1)$ into three equal parts. In Figure 1, those breakpoints are –0.5 and 0.5. Then, we assign the symbols to the three different areas defined by the breakpoints.

Markov-switching models

An alternative to SAX is to apply a Markov switching model (MSwM). It is based on seeing the original series as transitioning between different *regimes* (or states) and using the probability distribution of the switches between them (Hamilton 1989, 1990). Each regime is denoted by a symbol in the STSA.

More precisely, consider a system transitioning between a finite number of states $1, \dots, N$ such that in any period $t \in N$, the distribution of possible instances of the variable s_t satisfies the following condition:

$$P\{s_t = j | s_{t-1} = i, s_{t-2} = k, \dots\} = P\{s_t = j | s_{t-1} = i\} = p_{ij}$$

where each p_{ij} corresponds to the probability of a transition from state j to state i; then, $p_{i1} + p_{i2} + \cdots + p_{iN} = 1$.

Now consider a time series $\{y_t\}_{t \geq 0}$. This means that if the values are drawn from a compact set Y, the distributions over Y at t, F_t, and at any period $t + k$, F_{t+k}, do not necessarily verify that $F_t = F_{t+k}$. The behavior of the series can be described as follows (Hamilton 1994):

$$y_t - \mu_{s_t^*} = \phi\left(y_{t-1} - \mu_{s_{t-1}^*}\right) + \varepsilon_s$$

where $\mu_{s_t^*} = E[Y_t \mid s_t^*] \in Y$ corresponds to the state $s_t^* \in \{1, \dots, N\}$. If $s_t^* = j$ and $s_{t-1}^* = i$, at $t-1$, μ_i is followed in t by μ_j, with $\mu_i \neq \mu_j$. The transition from $\mu_{s_{t-1}^*}$ to $\mu_{s_t^*}$, corresponding to the transition from state j to state i, has probability p_{ij}. Thus, ϕ is a function that embodies the combined action of P and, for each state i and period t, the conditional distribution $F_t(y|i)$. Then, any time series can be reduced to a sequence of states.

The main idea behind this method is that it is assumed that a number of states or regimes guide the evolution of the series. Assuming that each regime yields a certain range of values of the series, the mean value of the values in each such range yields the corresponding value that, in a transformed series, replaces each observation under that particular regime. Given that a finite number of regimes are assumed to exist, the new series is piecewise linear with each „flat" segment corresponding to a regime.

Methodology

While in principle it is easy to apply the STSA approach, a variant is needed to characterize *contemporaneity* as a synchronic change in structure. We start by considering a time series X of T periods, transforming it into a symbolic series of two/three states. To ensure the robustness of our results, we proceed by finding the symbolic series using both Markov switching and SAX, although other methods could also be used to detect regime switches in time series, such as break estimation (Bai–Perron 1998). The presence or absence of such robustness is one of the key features for the search for contemporaneity, since the simultaneity of changes in regimes depends critically on how the regimes are characterized.

Then, to assess the contemporaneity of two series X and Y, we proceed as follows:

- Given the symbolic version of a series X, denoted **X,** a new series X' can be generated of length T–1 such that X'(t) = –1 if **X**(t–1) = **X**(t) (i.e., X(t–1) and X(t) are assigned the same symbol), and X'(t)=1 otherwise.
- In the same way, a series Y' is generated from series Y.
- The contemporaneity of X and Y is evaluated by comparing the values of the derived series X' and Y'.

For instance, if we intend to assess the contemporaneity of the GDP processes of several countries, we start by considering for each country the time series of GDP growth. Suppose further that we generate a symbolic time series with two states, high (H) and low (L). This yields a series such as HHLHLHHL (here of length 8). We then transform this series into a derived series (of length 7): (–1)1111(–1)1.

Given the series of GDP growth of two countries of length T, we find their corresponding series of switches 1 or –1 and transform the latter ones into vectors of dimension T–1. To compute the contemporaneity, we compute the scalar product of these two vectors (that is, an operation that given the two vectors returns a single value). The resulting real number can be identified with the *synchronicity correlation* between the growth time series of the two countries. A higher value indicates a more frequent occurrence of contemporary regime switches.

It becomes harder to extend this characterization of contemporaneity to more than two time series. In the case of our example, for more than two countries, we fix an ordering of the countries to proceed computing the contemporaneity by pairs in the given order. Therefore, for instance, if we intend to measure the contemporaneity between Argentina (ARG), Brazil (BRA) and Chile (CHL), if we order them as ARG-BRA-CHL, we proceed by comparing ARG-BRA and then BRA-CHL. If, instead, the order is ARG-CHL-BRA, we will compare ARG-CHL and CHL-BRA. This distinction matters since we aggregate the overall contemporaneity of the class of countries by summing the pairwise measures. Thus, the aggregate contemporaneity depends on the ordering between the countries.

To find the maximal aggregate contemporaneity, we must examine all possible orderings. The highest aggregate contemporaneity is obtained in an ordering in which the most relevant countries are usually those in the middle of the ordering, while countries with more atypical regime switching behaviors tend to be placed closer to the top and bottom of the linear ordering of countries.

An important part of the analysis, when more than two series are involved, consists of finding their optimal ordering. For that, we simulate all possible orderings until the one yielding the highest aggregate contemporaneity is found. Of course, this procedure is computationally costly, and for a very large number of series, it may be practically infeasible. Nevertheless, for regional data and considering only the series that may be theoretically associated, the procedure can run fast enough on commonly available computers.

Our proposed methodology is not a mere extension of the symbolic series or regime switching methodologies. It uses those techniques to build the regime series to detect the time periods at which they show breaks or changes, but it could be adapted to use any other methodology of transformation of time series to generate derived series with which a contemporaneity index could be computed.

For the estimation of the Markov switching models and the SAX regime detection, we used the R language and the R packages *msmFit* and *seewave*, respectively [1-2].

Empirical application: Economic growth and investment regimes in South America

To illustrate our method, consider first the economic growth series of some Latin American countries drawn from the World Bank database (WB). More specifically, for the 1960–2018 period, we take the series of Argentina, Bolivia, Brazil, Chile, Colombia, Ecuador, Peru, Paraguay and Uruguay. The series are exhibited in Figure A1 in the Appendix.

As shown in Figure A1, the similarity among the general trends of the GDP series in the studied region seems to be high. We can also see in Table A1 in the Appendix that the distribution is very similar, agreeing with the casual visual evidence. Furthermore, Table A2 in the Appendix shows that the series are correlated, even those that exhibit marked nonlinearities. Despite this evidence of close association, we want to dig further in the data to analyze the contemporaneity between the behavior of the GDP series of these countries to see whether these relations remain under this analysis.

For each country, we compute the best Markov switching approximation using the Akaike information criterion. Then, we transform this symbolic series into a derived time series of switches as described in the previous section. We also do the same using SAX.

Then, we find the highest aggregate contemporaneity values for the whole sample and by decade (to capture the possible variation of synchronicities among countries over time) with some overlap to ensure a smooth transition between decades. The results obtained for the series obtained using Markov switching can be seen in Tables A3 and A4 in the Appendix. These tables show the ordering among countries and the corresponding values of contemporaneity, respectively. In turn, Tables A5 and A6 in the Appendix present analogous results for the series obtained by applying SAX.

We can see that the STSA yields very different results under Markov switching and SAX. The aggregate contemporaneity with the former is more than twice that with the latter. This is not surprising, considering that SAX assigns the same value to all the periods in a time bin, which in the case of high variance of values hides the ensuing fluctuations. This, in turn, leads to a rather regular series of switches and thus to fewer matches among the switches in two countries. Markov switching, instead, better captures the inner workings of growth processes, capturing the switches from one regime to another.

Taking this into account, we can focus on the results of Tables A3 and A4 in the Appendix. We can see that for the full sample and the entire period, the highest contemporaneity indices arise for the Andean countries (except Peru) and Brazil. In contrast, Argentina and Peru exhibited less synchronicity with other economies. Argentina, Brazil and Peru suffered hyperinflation and recessions (Felix 1990). However, Argentina and Peru experienced "lost decades", while Brazil saw its influence and reach grow during the period under analysis.

Notice that the first decade (the 1960s) shows a slightly different picture, in which the Andean countries (including Peru) were also highly synchronized, but Argentina and Brazil were rather uncoupled. The last period (2006–2018) shows a strong presence of Chile and a low coupling of Paraguay. These countries experienced sustained growth processes in those years (Hossain–Rokonuzzaman 2018).

As a second, closely related example, consider the series of investment of the same countries, depicted in Figure A2 in the Appendix, and their corresponding descriptive statistics in Table A7 as well as their correlation values in Table A8 in the Appendix. As in the previous case, the ups and downs of the series seem to be synchronized at first glance.

If we repeat the empirical exercise of evaluating the contemporaneity indices for the investment series (from the same WB source for the 1970–2018 period), we find the results presented in Tables A9 to A12 in the Appendix.

As we can see, the results are not the same as with the GDP example. Some orderings are similar, but in general, the relations are different. For example, when analyzing the GDP series, Argentina shows a higher contemporaneity with Brazil (24 periods) or Uruguay (23), while in the case of investment, Argentina has more similarities with Paraguay (29 or 44 depending on the methodology employed to build the regimes). These disparities indicate that in the case of specific changes, the relations between the same variables in different countries of the same region may behave quite differently, even if the correlations are high.

In the case of GDP and investment, while the latter seem to be a highly relevant cause of the former, a Granger test (see Table A13 in the Appendix) indicates the absence of such a relation for both Argentina and Paraguay[2]. This may explain why, as indicated above, Argentina seems to be more similar to Paraguay in terms of the contemporaneity of changes in investment but not in those of the growth rate. This is further supported by a Granger causality test that indicates that the investment series of these two countries cause each other, while the growth series of Argentina and Paraguay seem to be causally unrelated. This may allow a further analysis of the differences in the growth processes of these countries seeking to detect the factors that promote or hamper regime changes in the variation of GDP.

Conclusions

We have presented here a characterization of the *contemporaneity* of two time series in terms of their switches in the corresponding symbolic versions. We extend this to a notion of *aggregate contemporaneity* for more than two time series.

A key element for these definitions is the derivation of the symbolic versions of the time series. We explored two ways of doing this in a systematic form by using either the Markov switching approach or symbolic aggregate approximation (SAX). Both require arbitrary choices to be made by the analyst but endogenize the structure of the set of symbols and the assignation of ranges of values to each symbol.

For the definition of contemporaneity, Markov switching has an advantage since it better captures the switching between regimes, while SAX tends to hide them if the

[2] For the Granger test, we use the MSBVAR package in R, and the function granger.test [3-4].

time bins chosen by the analyst are not short enough. In either case, finding the right aggregate contemporaneity index requires exploring different linear orderings of the class of time series.

The application to the analysis of the growth of GDP and investment time series (using the Markov switching approach) allows us to detect regional patterns in the process, in particular the existence of coupled economies as well as those that exhibit atypical behavior. In the case of South American countries, this analysis allowed the detection of the rising influence of Brazil, the pervasiveness of crises in Argentina and the rapid development of the Chilean economy.

The consequences of detecting the differences in the moments at which regime changes happen and the consequent lack of synchronization among countries pose several new research questions such as why seemingly closely associated series may not share the same regime break structure, or what causes the lagged responses to changes in the cases in which, despite the regional identification, the contemporaneity index is rather low? An even deeper question arises in light of the evidence provided by the contemporaneity index, namely, what degree of contemporaneity is needed to claim that a group of countries constitutes a region? This is a matter for future research, in which, in addition to using the contemporaneity index, other tools, both theoretical and empirical, will be needed.

With respect to the measure presented here, further analysis amounts to redefining aggregate contemporaneity by a procedure different from adding pairwise contemporaneity indices, applying a multivariate version of Markov switching (Eo–Kim 2016). Another possibility is to cluster series in terms of their "closeness" according to their respective contemporaneity indices.

Such an improved version of our approach may provide a tool for a finer analysis of regional phenomena, contributing to the detection of synchronisms among the processes in different components of the regions (see, for instance, Preciado–Torrero 2021, Purwono et al. 2021, Maulana–Aginta 2022, Duran–Karahasan 2022).

Further research is also needed to develop some kind of approximation algorithm to guarantee the correct ordering of the chain contemporaneity relations in the case of a larger database of regional information, with an increasingly longer series.

Appendix

Figure A1

GDP per capita growth (%): World Bank data series

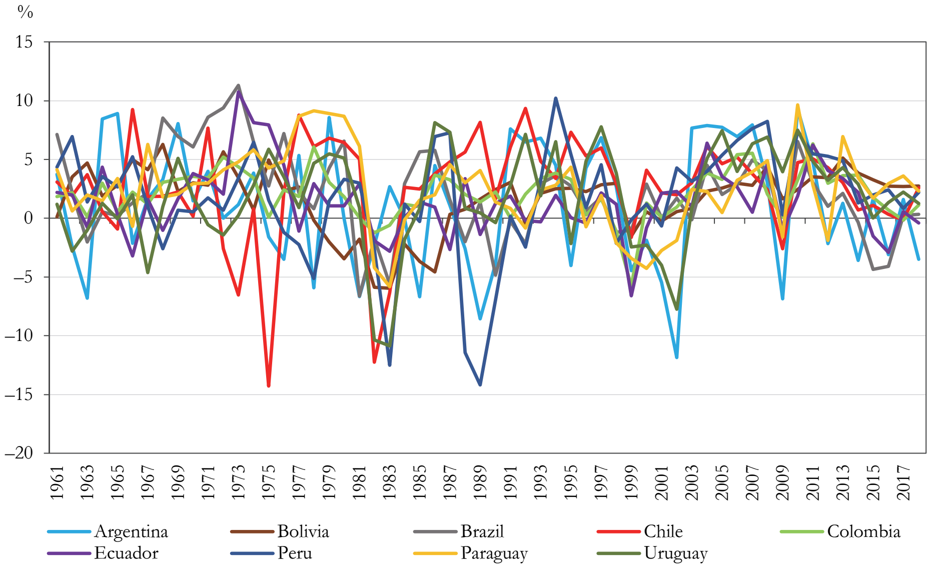


Figure A2

Investment series (%GDP): World Bank data series

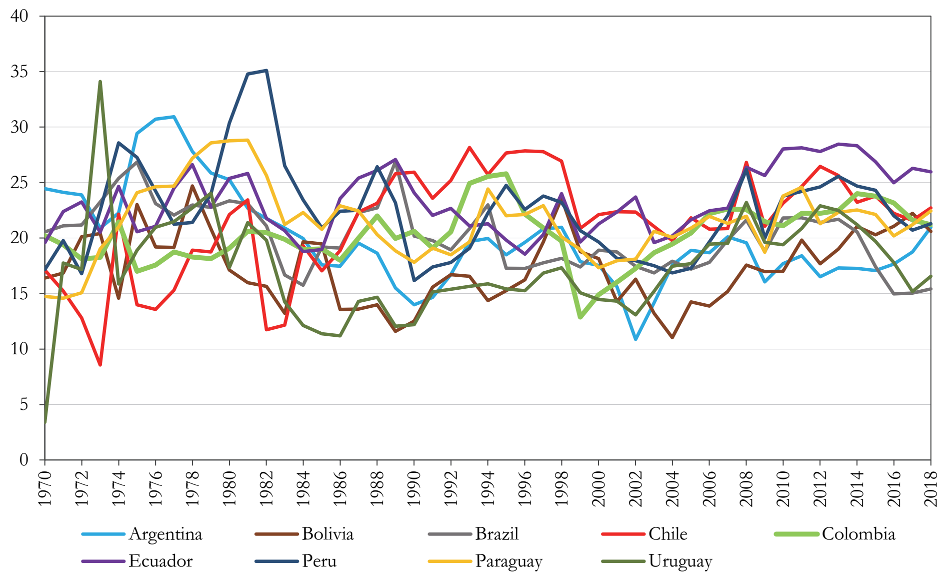


Table A1

Economic growth descriptive statistics

Country	Min	1Q	Median	Mean	3Q	Max
Argentina (ARG)	–11.85	2.98	1.54	1.13	5.21	9.3
Bolivia (BOL)	–5.95	0.55	2.47	1.66	3.05	6.28
Brazil (BRA)	–6.62	–0.09	2.06	2.11	4.44	11.3
Chile (CHL)	–14.25	1.25	3.02	2.61	5.16	9.34
Colombia (COL)	–5.76	0.95	2.11	2.09	3.33	6.32
Ecuador (ECU)	–6.61	–0.37	1.49	1.51	2.93	10.75
Peru (PER)	–14.18	0.2	1.85	1.65	4.81	10.22
Paraguay (PRY)	–5.83	0.67	2.63	2.45	4.23	9.64
Uruguay (URY)	–10.85	–0.03	1.85	1.79	4.85	8.12

Table A2

GDP PC growth series correlation

Country	ARG	BOL	BRA	CHL	COL	ECU	PER	PRY	URY
Argentina (ARG)	1.00	0.12	0.29	0.17	0.34	0.18	0.33	0.20	0.45
Bolivia (BOL)	0.12	1.00	0.20	0.10	0.32	0.27	0.26	0.23	0.28
Brazil (BRA)	0.29	0.20	1.00	0.05	0.51	0.45	0.36	0.38	0.27
Chile (CHL)	0.17	0.10	0.05	1.00	0.32	–0.14	0.11	0.27	0.39
Colombia (COL)	0.34	0.32	0.51	0.32	1.00	0.50	0.33	0.49	0.43
Ecuador (ECU)	0.18	0.27	0.45	–0.14	0.50	1.00	0.26	0.35	0.29
Peru (PER)	0.33	0.26	0.36	0.11	0.33	0.26	1.00	0.21	0.42
Paraguay (PRY)	0.20	0.23	0.38	0.27	0.49	0.35	0.21	1.00	0.46
Uruguay (URY)	0.45	0.28	0.27	0.39	0.43	0.29	0.42	0.46	1.00

Table A3

Markov-Switching orders (C-i indicates the i-th country in the order)

Time interval	C-1	C-2	C-3	C-4	C-5	C-6	C-7	C-8	C-9
1961–1970	ARG	URY	PER	BOL	COL	PRY	ECU	CHL	BRA
1970–1979	COL	URY	PRY	ECU	ARG	BRA	CHL	PER	BOL
1979–1988	BOL	CHL	PRY	PER	ECU	ARG	URY	COL	BRA
1988–1997	BRA	URY	BOL	ECU	CHL	ARG	COL	PER	PRY
1997–2006	URY	BOL	PER	ECU	BRA	CHL	PRY	COL	ARG
2006–2018	BOL	PRY	PER	ARG	BRA	ECU	URY	COL	CHL
Full Sample	PER	PRY	CHL	BRA	ECU	BOL	COL	URY	ARG

Table A4

Markov-Switching synchronicity index (C-i/C-(i+1) indicates the contemporaneity between the i-th and the (i+1)-th country in the order)

Time interval	C-1/C-2	C-2/C-3	C-3/C-4	C-4/C-5	C-5/C-6	C-6/C-7	C-7/C-8	C-8/C-9
1961–1970	4	6	8	10	10	10	10	6
1970–1979	6	4	8	2	0	6	4	4
1979–1988	2	8	–2	2	8	4	2	6
1988–1997	10	10	10	10	2	2	4	6
1997–2006	6	6	6	10	10	6	2	2
2006–2018	2	0	4	10	12	12	12	12
Full Sample	21	33	43	47	49	45	35	23

Table A5

SAX orders (C-i indicates the i-th country in the order)

Time interval	C-1	C-2	C-3	C-4	C-5	C-6	C-7	C-8	C-9
1961–1970	PRY	BRA	ARG	CHL	PER	COL	ECU	BOL	URY
1970–1979	PER	ECU	ARG	PRY	URY	BOL	CHL	COL	BRA
1979–1988	CHL	BOL	URY	COL	PRY	ECU	ARG	PER	BRA
1988–1997	BRA	PRY	URY	COL	ECU	CHL	ARG	BOL	PER
1997–2006	PER	COL	PRY	URY	BOL	BRA	ECU	ARG	CHL
2006–2018	ARG	COL	URY	BRA	CHL	BOL	PRY	ECU	PER
Full Sample	ARG	BRA	PRY	COL	CHL	PER	URY	BOL	ECU

Table A6

SAX synchronicity index (C-i/C-(i+1) indicates the contemporaneity between the i-th and the (i+1)-th country in the order)

Time interval	C-1/C-2	C-2/C-3	C-3/C-4	C-4/C-5	C-5/C-6	C-6/C-7	C-7/C-8	C-8/C-9
1961–1970	2	6	6	4	2	4	4	4
1970–1979	0	4	–4	8	6	2	2	2
1979–1988	6	4	6	0	6	0	–2	2
1988–1997	8	0	2	–2	4	4	6	–6
1997–2006	6	6	4	6	4	0	2	4
2006–2018	7	3	–1	3	1	–3	–3	–1
Full Sample	24	20	14	18	18	12	22	12

Table A7

Investment descriptive statistics

Country	Min	1Q	Median	Mean	3Q	Max
Argentina (ARG)	10.85	17.46	18.89	19.86	20.97	30.94
Bolivia (BOL)	11.02	14.58	16.97	17.3	19.67	24.69
Brazil (BRA)	14.97	17.79	20.17	20.11	22.07	26.9
Chile (CHL)	8.55	18.91	22.15	21.31	24.64	28.14
Colombia (COL)	12.88	18.75	20.44	20.31	22.15	25.8
Ecuador (ECU)	18.54	21.06	22.79	23.34	25.83	28.47
Peru (PER)	16.16	19.65	22.42	22.5	24.31	35.1
Paraguay (PRY)	14.56	19.11	21.3	21.44	22.9	28.83
Uruguay (URY)	3.39	15.07	17.15	17.33	19.7	34.11

Table A8

Investment series correlation

Country	ARG	BOL	BRA	CHL	COL	ECU	PER	PRY	URY
Argentina (ARG)	1.00	0.42	0.44	–0.50	–0.17	–0.11	0.34	0.43	0.28
Bolivia (BOL)	0.42	1.00	–0.02	–0.15	–0.11	0.18	0.12	0.23	0.39
Brazil (BRA)	0.44	–0.02	1.00	–0.16	–0.06	0.28	0.40	0.28	0.29
Chile (CHL)	–0.50	–0.15	–0.16	1.00	0.49	0.31	–0.06	0.03	–0.20
Colombia (COL)	–0.17	–0.11	–0.06	0.49	1.00	0.31	0.19	0.15	0.10
Ecuador (ECU)	–0.11	0.18	0.28	0.31	0.31	1.00	0.27	0.24	0.32
Peru (PER)	0.34	0.12	0.40	–0.06	0.19	0.27	1.00	0.67	0.33
Paraguay (PRY)	0.43	0.23	0.28	0.03	0.15	0.24	0.67	1.00	0.41
Uruguay (URY)	0.28	0.39	0.29	–0.20	0.10	0.32	0.33	0.41	1.00

Table A9

Investment: Markov-Switching orders (C-i indicates the i-th country in the order)

Time interval	C-1	C-2	C-3	C-4	C-5	C-6	C-7	C-8	C-9
1970–1979	ECU	PRY	PER	CHL	URY	ARG	COL	BRA	BOL
1979–1988	BRA	ARG	CHL	COL	URY	PRY	ECU	PER	BOL
1988–1997	PER	BOL	URY	CHL	BRA	PRY	ARG	ECU	COL
1997–2006	ARG	ECU	COL	URY	CHL	PER	BOL	BRA	PRY
2006–2018	URY	BRA	PER	ARG	PRY	ECU	CHL	COL	BOL
Full Sample	BOL	ARG	PRY	PER	URY	COL	BRA	CHL	ECU

Table A10

Investment: Markov-Switching synchronicity index (C-i/C-(i+1) indicates the contemporaneity between the i-th and the (i+1)-th country in the order)

Time interval	C-1/C-2	C-2/C-3	C-3/C-4	C-4/C-5	C-5/C-6	C-6/C-7	C-7/C-8	C-8/C-9
1970–1979	6	8	10	8	8	10	10	4
1979–1988	8	8	10	8	6	2	0	4
1988–1997	8	8	8	6	8	10	8	6
1997–2006	10	6	8	8	10	8	6	8
2006–2018	9	7	11	11	9	9	9	7
Full Sample	32	42	44	36	38	40	40	32

Table A11

Investment: SAX orders (C-i indicates the i-th country in the order)

Time interval	C-1	C-2	C-3	C-4	C-5	C-6	C-7	C-8	C-9
1970–1979	CHL	BRA	ARG	PRY	COL	URY	BOL	ECU	PER
1979–1988	BRA	ARG	CHL	COL	URY	PRY	ECU	PER	BOL
1988–1997	PER	BOL	URY	CHL	BRA	PRY	ARG	ECU	COL
1997–006	ARG	ECU	COL	URY	CHL	PER	BOL	BRA	PRY
2006–2018	URY	BRA	PER	ARG	PRY	ECU	CHL	COL	BOL
Full Sample	PER	BRA	PRY	ARG	CHL	URY	COL	BOL	ECU

Table A12

Investment: SAX synchronicity index (C-i/C-(i+1) indicates the contemporaneity between the i-th and the (i+1)-th country in the order)

Time interval	C-1/C-2	C-2/C-3	C-3/C-4	C-4/C-5	C-5/C-6	C-6/C-7	C-7/C-8	C-8/C-9
1970–1979	8	10	8	8	8	4	4	2
1979–1988	0	2	4	0	6	4	4	2
1988–1997	2	8	10	4	4	8	6	2
1997–2006	0	2	6	0	2	6	8	4
2006–2018	1	7	3	7	1	7	5	9
Full Sample	25	23	29	25	21	25	19	27

Table A13

p values of the Granger tests (lags=3)

	INV ARG	INV PRY	G ARG	G PRY
INV ARG		0.061	0.335	0.871
INV PRY	0.035		0.244	0.381
G ARG	0.176	0.353		0.592
G PRY	0.344	0.487	0.691	

Notes: Rows cause columns. INV and G denote Investment and Growth, respectively.

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