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RESEARCH ARTICLE

Latin American Falls and Rebounds since the COVID-19*

Luciano Campos[†] Danilo Leiva-León[‡] Steven Zapata-Álvarez[§]

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Abstract

This paper proposes comprehensive measures of the Latin American business cycle that help to infer the expected deepness of recessions, and strength of expansions, as they unfold in real time. These measures are based on the largest country economies in the region by accounting for intrinsic features of real activity, such as comovement, nonlinearities, asymmetries, and are also robust to unprecedented shocks, like the COVID-19 pandemics. The proposed measures provide timely updates on (i) inferences on the state of the regional economy and (ii) the underlying momentum embedded in short-term fluctuations of real activity. We evaluate as well the time-varying effects of U.S. financial conditions on the Latin American economy by employing the proposed measures and identify periods of persistent international spillovers.

Keywords: Business Cycles, Factor Model, Nonlinear, Latin America.

JEL codes: E32, C22, E27.

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†CONICET-Instituto Interdisciplinario de Economía Política, Facultad de Ciencias Económicas, Universidad de Buenos Aires. luciano.campos@economicas.uba.ar

‡European Central Bank. Danilo.Leiva-Leon@ecb.europa.eu

§Banco de la República. szapatal@banrep.gov.co

1. Introduction

Business cycles' predictions have been at the center stage of economic analysis since the seminal work of Burns and Mitchell (1946). For policy makers, it is of utmost importance to have a timely assessment of aggregate activity which they can shape their policies with. Due to recent turbulent events, such as pandemics or global geopolitical tensions, policy makers are facing economic environments that require continuous re-assessment. Consequently, considerable effort has been devoted to the design of sophisticated models able to provide timely measurements of the business cycle and identification of turning points, i.e., periods in which an economy transitions from an expansion to a recession or *vice versa*.

Most of the work on measuring economic activity in real time has been focused on developed economies and limited research has been dedicated to developing ones. In particular, Latin America has not been broadly studied yet at the aggregate level. If anything, previous works have been more of a country-specific rather than a comparative nature (Chauvet, 2001; Misas and Ramírez, 2007; Camacho et al., 2015; González-Astudillo and Baquero, 2019; Gálvez-Soriano, 2020). This turns out to be a pitfall when it comes to Latin American countries, because they share strong commonalities in their business cycles. Not only are they subject to similar external shocks, but also regional integration has deepened since the 1990's, as trade and financial links have strengthen within the region. Likewise, macroeconomic stability became much more widespread than in the past, when hyperinflationary crises were generalized. As a result, Latin America has exhibited highly coordinated business cycles over the last decades, as shown in Camacho and Palmieri (2017). Although previous works focus on assessing turning points and understanding the cyclical behavior of the world economy (Camacho and Martinez-Martin, 2015; Ferrara and Marsilli, 2019), a related literature for the case of the Latin American economy, as a whole, is nonexistent, as far as we are concerned.[1]

In this paper, we propose new measurements for the Latin American (LATAM) business cycles with the aim of improving real-time assessments of expected downturns and recoveries, that is, as they develop, allowing policy makers to timely update their optimal response to shocks. These measures inform about the economic weakness or strength on a timely basis, and quantify time-varying downside or upside risks to real activity growth in the region. Also, the proposed measures can be updated as soon as a new piece of information is released by statistical agencies, and are robust to the presence of highly nonlinear dynamics in real activity. This is specially convenient when analyzing emerging markets, since a central feature of their business cycles is their nonlinearity (Jerzmanowski, 2006; Aguiar and Gopinath, 2007).

We rely on the empirical framework recently proposed by Leiva-León et al. (2021) to build the proposed measures. The main advantage of this approach *vis à vis* previous methods is the use a Markov-Switching Dynamic Factor (MS-DF) model that is flexible enough to accommodate for heterogeneous expansions and recessions. Thanks to its flexibility, the model is apt to track down recessions and expansions of different magnitudes, which turns out to be an essential feature since the outbreak of the COVID-19 pandemic. The MS-DF model is fitted to eight of the largest LATAM economies: Argentina, Bolivia, Brazil, Chile, Colombia, Ecuador, Mexico and Peru. By including as input information on quarterly real GDP and monthly economic indicators for the corresponding economies, the model delivers as output both an index of real activity and the implied time-varying probability of an economic recession for each country.

[1] Instead, there is fruitful a literature that focuses on nowcasting purposes, rather than on turning points assessments or business cycles characterization, for Latin American countries. For example, Blanco et al. (2017) provide nowcasts of quarterly GDP of Argentina by employing dynamic factor models. León and Ortega (2018) focus on nowcasting economic activity in Colombia using information on electronic transfers and checks' payments among individuals, firms, and the central government. Pérez (2018) employs Stochastic Search Variable Selection to assess the most helpful leading indicators in order to nowcast GDP of Peru. Recently, Sampi and Jooste (2020) employ information on Google mobility reports to nowcast monthly industrial production in selected Latin American countries by relying on MIDAS regressions.

We summarize these country-specific inferences into two indices that provide an accurate and comprehensive picture of the state of the LATAM economy in real time. The first of them is the Latin American Weakness Index (LAWI), which quantifies the fraction of the region that faces a recession in a given month. Because it is calculated as a weighted average of the recession probabilities across countries, the LAWI can be interpreted as the probability of a regional economic recession in LATAM. This index suits the purpose of assessing the regional economic performance at a given moment in time, which becomes appropriate if it is assumed rising business cycle connectedness during global crises (Diebold and Yilmaz, 2015). In fact, the LAWI recognizes two periods of complete synchronization of Latin American economies which correspond to the "Great Recession" of 2008-2009 and the recent contraction induced by the COVID-19 pandemics. It also identifies several periods of decoupling when only part of the region exhibited a recessionary phase. Moreover, the historical decomposition of the LAWI offers a clear guidance about the countries that contribute the most to LATAM economic weakness over time.

Given that the LAWI represents a fraction that is bounded between zero and one, it is uninformative on the intensity of the crises or the booms. Therefore, we propose a second index, referred to as the Latin American Momentum Index (LAMI), that quantifies the size of the falls and rebounds of economic activity in the region, and that is based as a weighted average of the expected expansionary and recessionary growth rates associated with all the economies under consideration. Our estimates illustrate the uniqueness of COVID-19 crisis, which was about twice as deep as that of the "Great Recession", though less persistent, for the Latin American economy. Also, the recovery after the eased of the lockdown measures has no precedent in the last twenty five years. However, this rebound was loosing strength by the time of writing this paper.

Both indices aim to provide a practical set of information for policy makers and pundits in delivering a comprehensive characterization of LATAM's business cycle on a timely basis. The usefulness of these new measurements, or indices, relies in that they can provide accurate regional economic outlook in real time, as new information associated with each country is released. To our true knowledge, there is no framework like the one proposed in this paper available for LATAM economies.

In addition, we present an empirical application that illustrates one possible alternative use of the proposed indices, other than monitoring purposes. In particular, we explore how U.S. financial conditions influence medium-term economic fluctuations in the LATAM economy. This analysis is meaningful in that U.S. monetary shocks have been typically considered a relevant source of business cycles in the LATAM region (Canova, 2005). Our results show that tighter U.S. financial conditions have significant and time-varying negative effects on LATAM's medium-term growth of real activity. In particular, the evidence suggests that tighter U.S. financial conditions impacted significantly on the region at the end of the 1990's, during the Subprime crisis and since the outbreak of the COVID-19 pandemic.

Finally, we believe that this work can contribute to a continuous monitoring of economic activity, that can lead policymakers to make better, more informed and timely public policy decisions. The economic strength and risks associated with the Latin American region is of high importance, especially for international organizations such as the International Monetary Fund, the World Bank and the Bank for International Settlements, among many others. This type of information allows policy makers to put the LATAM region into perspective when compared with advanced economies or other emerging markets, which is key to identify the latent vulnerabilities that the world economy may be experiencing and, consequently, to provide a more accurate global outlook.

The rest of the paper is organized as follows. Section 2 highlights the advantages of the empirical methodology employed in this paper when compared to previous frameworks typically used in the literature. Section 3 presents the new indices for the measurement of LATAM's business cycles, which constitute the main contribution of our work. Section 4 shows the empirical application of the proposed indices regarding how U.S. financial conditions affect LATAM economy. Finally, section 5 concludes.

2. Inferring turning points since the COVID-19

A key feature we have considered when building our indices is the unparalleled severity of the COVID-19 crisis and the subsequent sizable rebound in activity when lockdown measures were eased. Figure 1 shows the GDP growth rates for a selected group of Latin American countries (Brazil, Mexico and Peru) prior the COVID-19 pandemics (top chart) and including that period (bottom chart). This figure highlights that GDP growth rates had unusual magnitudes since the COVID-19 outbreak, and this picture is quiet representative for the rest of the economies in the region (and the world) as well.

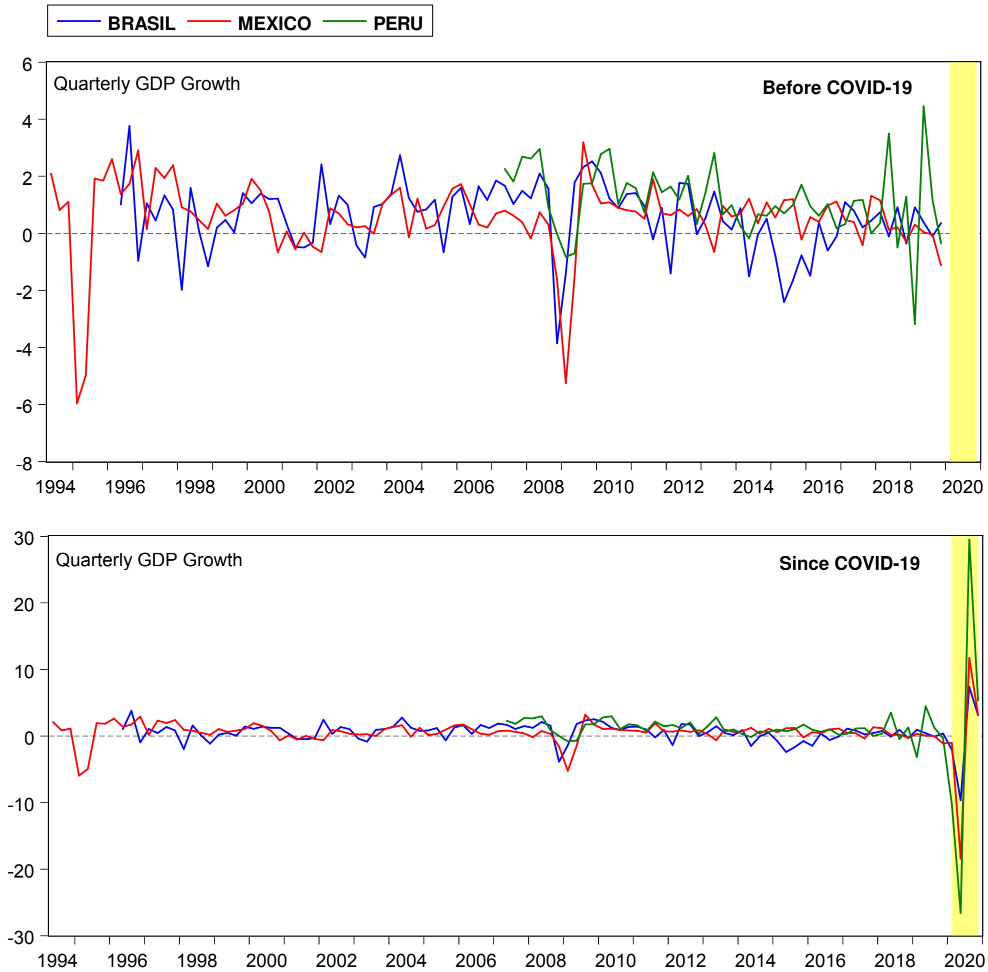

Figure 1: *GDP growth in LATAM selected countries before and since the COVID-19*

Source: National Statistics Institutes. See the Online Appendix A for details.

This unprecedented event precludes policy makers and pundits from resorting to the typical practitioner's toolkit conceived to track turning points, because of its inability to accommodate the type of nonlinearities which arose during the COVID-19. As a matter of fact, commonly used frameworks to infer the state of an economy do not take into account the heterogeneity of growth exhibited both across recessionary and expansionary episodes. Now more than ever, forecasting models must be flexible enough to adapt to the fact that not all recessions (expansions) present the same degree of deepness (buoyancy). Actually, nonlinear models generally used for identifying turning points in a timely fashion

(Hamilton, 1989; Chauvet, 1998), assume that all peaks and troughs in a given sample are of the same magnitude. This feature can lead to distort inferences on turning points in the presence of extremely large magnitudes in the data, such as the ones observed in the bottom chart of Figure 1. Moreover, the evaluation of macroeconomic tail risks become more challenging under a highly nonlinear economic environment. Empirical frameworks typically used to infer tail risks, such as quantile regressions (Adrian et al., 2019), are also prone to generate a poor performance when facing large fluctuations in activity, like the ones exhibited during the COVID-19 crisis.

Hence, the technology employed in this paper to infer turning points in LATAM economies relies on the nonlinear dynamic factor model recently proposed by Leiva-León et al. (2021). This novel framework takes into account two intrinsic features of the business cycle, which are the comovement among real activity indicators and the asymmetries associated with expansionary and recessionary episodes. In particular, consider a set of indicators of real activity, $y_t = (y_{1,t}, ..., y_{i,t}, ..., y_{n,t})'$, for a given country. The aim of the model consists on decomposing each indicator into a common factor, f_t, and and idiosyncratic component, $u_{i,t}$, as follows.[2]

$$y_{i,t} = \gamma_i f_t + u_{i,t}, \tag{1}$$

where γ_i denotes the associated factor loading and the idiosyncratic component is assumed to follow an autoregressive process of order p,

$$u_{i,t} = \sum_{l=1}^{p} \psi_{i,l} u_{i,t-l} + e_{i,t}, \quad e_{i,t} \sim \mathcal{N}(0, \sigma_i^2). \tag{2}$$

The common factor summarizes the information contained in all the indicators and, therefore, can be interpreted as an index of real economic activity. It is crucial to acknowledge for the fact that each recession (and expansion) is of unique magnitude, and that our technology lets the common factor to exhibit a flexible nonlinear dynamics that account for this feature. Specifically, it is assumed that the common factor is composed of two parts,

$$f_t = \mu_t + \varepsilon_t, \quad \varepsilon_t \sim \mathcal{N}(0, \sigma_f^2). \tag{3}$$

The first part, μ_t, corresponds to the momentum of real activity, i.e. what is referred to as "real momentum", and measures the intensity of growth that an economy exhibits during a given episode of expansion or recession. The real momentum, μ_t, can be also interpreted as the medium-term growth trend of an economy, within an expansion or recession. Instead, the second part of the common factor, ε_t, refers to short-term (noisy) fluctuations around the momentum of activity, which are assumed to be $i.i.d.$

The decomposition of the common factor between momentum and noise components can be of high importance for policy makers in order to filter out temporal deviations of economic activity growth from its medium-term trend. This decomposition provides a more crystalline view on the strength of the economy, especially, when it is transitioning from one phase of the business cycle to another, which is exactly when more uncertainty tends to arise. This is particularly the case for Latin American economies, where real activity tends to be more volatile than in advanced economies and, hence, where it becomes more difficult to extract from the data precise and prompt assessments about the direction where the economy is heading to.[3]

[2]For ease of exposition, Equation (1) makes reference to data expressed at one frequency only, i.e. monthly. However, the empirical application of the model also includes information on quarterly GDP growth. In order to deal with mixed frequency data within the context of the factor models, we rely on the approach proposed by Mariano and Murasawa (2003), which consists on relate quarter-on-quarter growth rates of GDP as a weighted averaged of month-on-month growth rates of the common factor.

[3]Previous work by Antolín-Díaz et al. (2017) focus, instead, on measuring long-term growth of U.S. GDP by modeling it as a random walk. However, due to the assumed slow moving dynamics, such approach is not able to take into account for the asymmetries embedded in expansionary and recessionary phases.

The measure of real momentum is aimed to shed light on two questions: (i) is the economy experiencing a recession or expansion? and (ii) how deep/buoyant is being such a recession/expansion? Therefore, the model allows μ_t to evolve according to the following process,

$$\mu_t = \mu_{0,\tau_0}(1 - s_t) + \mu_{1,\tau_1} s_t. \tag{4}$$

The first question can be answered by the discrete latent variable $s_t \in \{0, 1\}$, that dictates the phase of the business cycle by taking the value of 0 when the economy is in a recession and the value of 1 during expansions. The variable s_t is assumed to follow a Markovian process of first order with transition probabilities assumed to be constant and given by,

$$\Pr(s_t = j|s_{t-1} = i, s_{t-2} = h, \ldots) = \Pr(s_t = j|s_{t-1} = i) = p_{ij}. \tag{5}$$

As for the second question, it can be answered by the regime-dependent means μ_{0,τ_0} and μ_{1,τ_1}, which denote the intensity of growth exhibited by the economy during the τ_0 recession or τ_1 expansion, respectively.

It is important to emphasize that the regime-dependent means, μ_{1,τ_0} and μ_{0,τ_1}, are recession- and expansion-specific, respectively, which is a novelty in the literature. In particular, this specification differs from Chauvet (1998), where the common factor means of recessions and expansions are assumed to be two constants. Additionally, our framework differs from that of Eo and Kim (2016) in that they are based on a univariate model that only considers GDP and imposes restrictions on the underlying regime-dependent means through random walk processes. In contrast, our approach does not constrain the means defined in Equation (4) to exhibit any time persistence. Specifically, we assume that $cov(\mu_{\iota,\tau\iota}, \mu\iota, \tau_\iota - j) = 0$ for all j and for $\iota = 0, 1$, indicating that the mean associated with a given regime is drawn from a unique distribution. This relaxation of the persistence assumption is important because it ensures that each regime-dependent mean is independent of its past values. This feature is particularly relevant when applying the model to economies that experience varying magnitudes of expansions and recessions, such as those observed during the COVID-19 crisis.

The model defined in equations (1)-(5) is estimated with Bayesian methods due to the highly nonlinear dynamics embedded in the system. Additional details on the model and the employed estimation method are reported in Online Appendix B for the sake of space.

3. New measures of the Latin American business cycle

The nonlinear factor model (1)-(5) is independently fitted to eight of the largest Latin American economies; Argentina, Bolivia, Brazil, Chile, Colombia, Ecuador, Mexico and Peru. For each country, we not only collect information on real GDP, but also on additional indicators that are available at the monthly frequency and have been typically used for the measurement of economic conditions, such as industrial production, exports, imports and consumption indicators, among others. The detailed list of indicators used to estimated the model associated with each country is reported in Table 2, located in Online Appendix A. It is important to note that the employed data do not contain pandemics-related indicators, neither are there financial indicators that could have helped predict the "Great-Recession" of 2008-2009. This is intentionally done with the aim of allowing the model to track any recession, independently on its underlying source, since the effect of the associated contractionary shocks must be reflected in some, if not all, of the employed indicators.

Once the model is estimated for each country, there are two primary objects to be retrieved, which correspond to the inferences on the state variable, s_t, and the common factor, f_t. The entire history of the recession probabilities across countries, which are not reported here but are available upon request, show that the employed model successfully infers recessions and expansions of different magnitudes for all countries, thanks to its time-varying regime-dependent mean.

It might be added that the definition of recessions used in this paper is closely linked to the one followed by the NBER in that it refers to a sequence of a relatively small number of periods (e.g. at least two quarters) of consecutive negative growth of real activity. However, it is worth mentioning that there is also a prominent literature, associated with structural macroeconomic models, that sometimes defines recessions as prolonged deviations of real activity from an unobserved trend component, that is, based on the output gap. In this respect, our inferred recessionary regimes can be also interpreted as regimes of low-growth of real activity. This is particularly the case for Latin American countries, which exhibit fluctuations in economic activity with higher frequency and more amplitude than the ones typically observed in advanced economies.

The second main object retrieved from the model is the common factor, or index of economic activity. The monthly indices corresponding to each particular country, which are not shown here but are available upon request, present two distinct features. First, the unparalleled decline in activity during the COVID-19 pandemics experienced by all the countries. Second, the noisiness of economic activity, which is a distinct feature of LATAM economies that is reflected in most representative indicators of real activity throughout the region. Hence, these indices are useful when one is interested in addressing short-term fluctuations in activity. However, if the aim is to infer the medium-term growth path of the economy, the component of f_t corresponding to the real momentum, i.e. μ_t, would provide an accurate signal.

By employing the country-specific estimates mentioned above, we proceed to describe two new measures of the LATAM business cycle that unveil different, though complementary, relevant economic features of the region. These features are associated with real-time (i) inferences on state of the regional economy and (ii) measurement of the momentum embedded in short-term fluctuations in activity.

3.1. Economic Weakness

The first aggregate measure proposed in this paper refers to the Latin American Weakness Index (LAWI), which estimates the evolving share of the LATAM economy facing a recession. The LAWI is constructed as a weighted average between the probability of recession associated to each country, $Pr(s_t = 0)$, where the weights are given by the relative size of the corresponding economy. Since the employed empirical framework is estimated in a Bayesian fashion, the l-th draw of the LAWI is defined as,

$$LAWI_t^{(l)} = \sum_{\kappa=1}^{K} \omega_{\kappa,t}(1 - s_{\kappa,t}^{(l)}), \tag{6}$$

where K makes reference to the number of countries under consideration. The collection of all draws, $l = 1, ..., L$, constitute the posterior density of the LAWI. Figure 2 reports the median of such posterior distribution as the estimate of the LAWI. This is an easy-to-interpret statistics that provides a continuous assessment of a qualitative feature, i.e., being in a regional recession or expansion. Particularly, when the LAWI exhibits values close to zero, it implies that the LATAM business cycle is presenting a solid expansionary face. Instead, when the LAWI shows values close to one, it means that the LATAM economy is facing a generalized recession embedded throughout the countries in the region. Consequently, values between zero and one reported by the LAWI make reference to the degree of economic weakness experienced by the Latin American region.

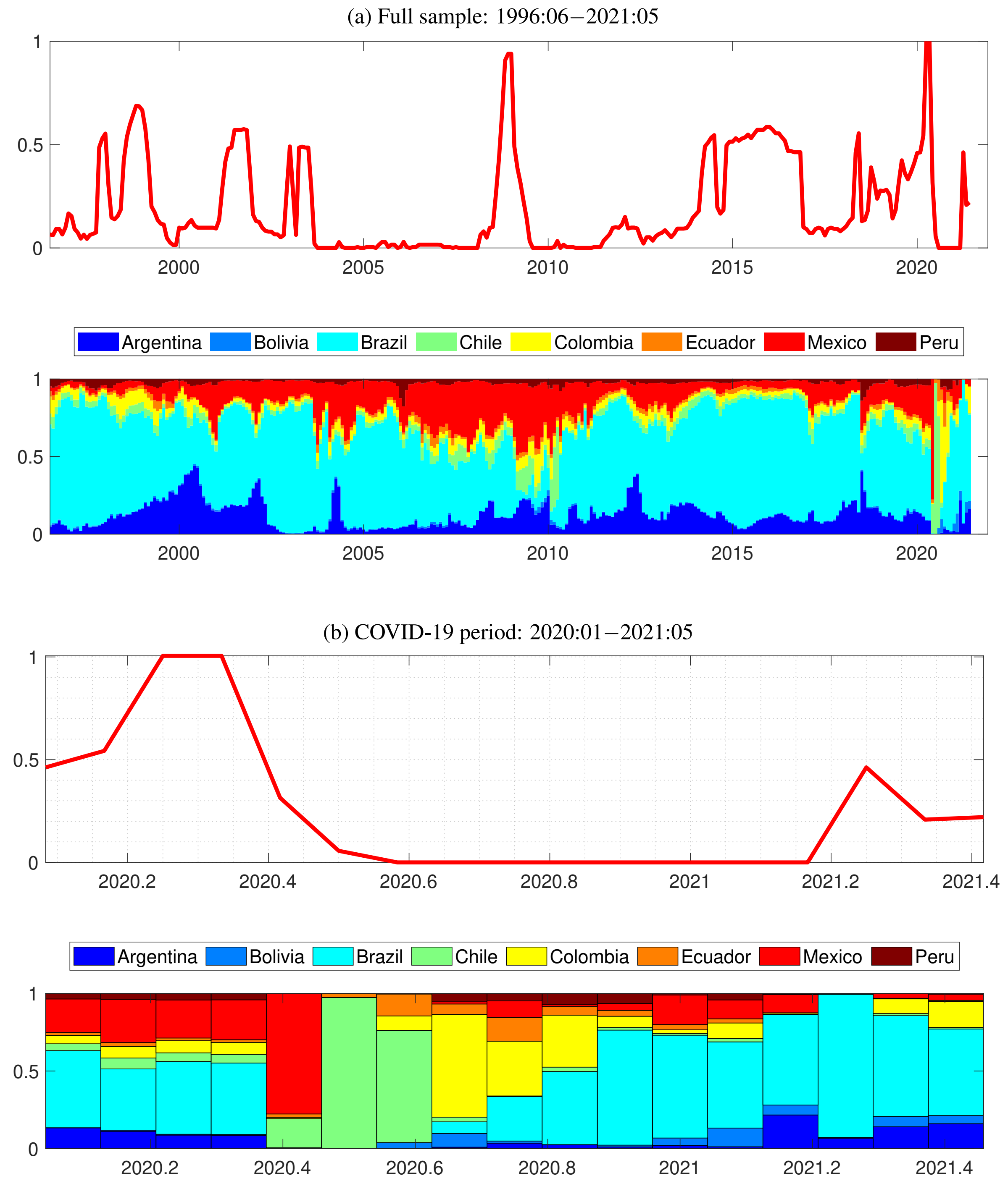

Figure 2: *Latin American Weakness Index (LAWI)*

Note. The upper figure of Chart A plots the LAWI for the period 1996:06−2021:05, which is constructed as a weighted average of the probabilities of recession across LATAM countries. The weights are given by the size of the corresponding economies. The lower figure of Chart A plots the normalized contributions of each country to the LAWI. The contribution of each country, at a given time, is defined as the product between the associated probability of recession and the weight of its economy, which is defined by the relative size in terms of GDP. Chart B plots the same information as in Chart A, but makes a zoom into the period 2020:01−2021:05.

Chart A of Figure 2 shows LAWI's evolution between 1996 and 2021 along with the corresponding historical contribution of each country to such weakness measure. The LAWI suggests that the region has gone through two clear episodes of recessions, which correspond to the "Great Recession" of 2008-2009 and to the recent "COVID-19 Recession." During these two episodes, the region was highly synchronized in a contractionary phase, yielding values of the LAWI close to one.

The LAWI also identifies additional periods of elevated degree of weakness, such as in the late 1990's and again in the early 2000's. The historical decomposition suggests that, during those years, the overwhelming influence of Brazil was complemented by an increase in that of Colombia and Argentina. This coincides with the idiosyncratic recessions suffered by these countries in 1999 and 2001, respectively. The period going from 2004 to 2014, with the relevant exception of the subprime crisis in 2008-2009, is associated with a low degree of weakness. This period corresponds to the so-called 2000s commodities super cycle, which played an important role in boosting aggregate activity in LATAM (Campos, 2019). At the end of the commodity boom, around 2014, the economic weakness hiked again, and some economies heavily dependent on oil, such as Brazil and Ecuador, lost momentum and entered a recession. The weakness of the LATAM economy remained at elevated levels during 2015 and 2016, mainly induced by Brazil, which was undergoing an important political and economic crisis around that time.

Chart B of Figure 2 makes a zoom into the economic contraction induced by the COVID-19 pandemics and the subsequent rebound. The chart also shows that the LATAM economy was already exhibiting a sizable degree of weakness prior to COVID-19 outbreak, with values of the LAWI around 0.5. Then, in February 2020 the LAWI started to rapidly increase reaching values close to one by March 2020, when all the countries were contributing uniformly to such a weakness. Further on, by April 2020, the LAWI began to decline induced by the reopening of activities in the region. Unlike the highly synchronized fall in activity throughout the region, the subsequent recovery was uneven across countries with their corresponding contributions substantially changing over time. In fact, Mexico and Chile played major roles during the turning point, as shown by the historical decomposition of the LAWI. This evidence can be explained by the swift vaccination campaign in Chile, while Mexico never truly apply a severe lockdown. Afterwards, during early 2021, LATAM exhibited a sizable, though temporary, increase on its economic weakness, mainly attributed to Brazil, Argentina and Colombia.

Overall, Figure 2 illustrates the rapidly changing economic environment in LATAM, especially in recent times. From a policy making perspective it is key to rely on a measure able to provide robust assessments on the regional economic weakness in a real-time fashion, that is, by using only the information available at the time of estimation. Hence, the LAWI can act as an early warning indicator of turning points in advance of how real activity might eventually evolve.

3.2. Growth Momentum

Despite the prompt signals that the LAWI can provide about a turning point in the region, it is unable to inform how deep an unfolding generalized recession in the region can get, or alternatively, how buoyant an expansionary face can become as it develops. This is because the LAWI, by measuring a fraction, is a bounded index between zero and one. Nevertheless, information about the deepness of an ongoing recession in LATAM is important for policy makers to optimally calibrate the appropriate response to crises as they evolve, e.g., in the context of coordination about fiscal stimuli or interest rate cuts. The same applies to expansionary periods, with opposite policy actions. A recent example of this, is the unprecedented deployment of policy expansion to counterweight the lockdown effects during the pandemic, followed by the abrupt policy contraction as inflationary pressure rose. Motivated by these needs, we propose the Latin American Momentum Index, also referred to as LAMI, that provides a measure of the how deep (buoyant) a recession (expansion) in Latin American can get as it is developing.

The LAMI is constructed as a weighted average of the growth momentum associated with each of the Latin American economies under consideration, that is μ_t, as defined in Equation (4), where the weights are set by the relative size of the corresponding country's economy. Given that the country-specific growth momentum, μ_t, is estimated in a Bayesian fashion, the l-th draw of the LAMI is defined as,

$$LAMI_t^{(l)} = \sum_{\kappa=1}^{K} \omega_{\kappa,t}\mu_{\kappa,t}^{(l)}, \tag{7}$$

where K makes reference to the number of countries under consideration. The collection of all draws, $l = 1, ..., L$, constitutes the posterior density of the LAMI. Note that the momentum is a comprehensive measure that contains information on both the turning points assessment, through s_t, and on the size of fall and rebounds that the economy exhibits, through μ_{0,τ_0} and μ_{1,τ_1}. The Bayesian estimation procedure employs a Gibbs sampler with the Carter and Kohn algorithm to produce latent variables, such as the growth momentum μ_t, through two steps: the Hamilton filter and simulation smoother. Consequently, the estimates of the latent variables obtained in-sample are smoothed. Also, due to the Bayesian estimation, it is possible to recover not only the point estimate of the index, but also the entire distribution, which can be used for a risk assessment[4].

Chart A of Figure 3 shows the Latin American Momentum Index along with the corresponding posterior density. The estimates point to three types of LATAM recessions in terms of deepness, that is, "small", "large" and "very large". In particular, the two recessionary episodes occurred during the late 1990s and early 2000s were consistent with recessions of "small" deepness, with the LAWI taking values of about -0.5 standard units. This was also the case during the recession induced by commodity prices in the mid 2010s. However, the "Great Recession" of 2008-2009 can be categorized as one of "large" deepness, with the LAMI exhibiting values of around -1 standardized units. Even more, the recent contraction induced by the COVID-19 pandemics falls into the category of "very large" deepness, with LAMI taking values twice as large as that of the "Great Recession" and four times as large as that of the commodities-driven recession in the mid 2010s.

In terms of economic expansions, the LAMI identifies two types that can be labeled as "normal" and "abnormal" episodes of positive growth. The most common, or "normal", expansionary phases are associated with LAMI values slightly below 0.5 standardized units. This is the average growth rate exhibited by the LATAM region during all expansions, with one important exception that corresponds to the "abnormal" growth that the region exhibited during the second half of 2020, right after the collapse in activity. During this "abnormal" expansionary phase the LAMI exhibited values above one standardized unit, that is, more than twice as large as a "normal" expansion in the region.

Overall, the LAMI provides a characterization of both recessionary and expansionary episodes in the LATAM economy. In this respect, two types of asymmetries of the LATAM business cycle are unveiled. First, recessions are more heterogeneous over time than expansions, in terms of their magnitudes. Second, "abnormal" expansions can be twice as large as "normal" ones, while "very large" recessions can be four times as large as "small" recessions in the region.

In order to assess the robustness of the LAMI when confronted to a real-time environment, the index is recursively estimated by adding one month of information at a time, for the period 2007:07-2021:05. Estimates of the real-time LAMI are reported in Chart B of Figure 3, showing that it is able to provide timely assessments on the size of falls and rebounds of the LATAM economy as they develop. It is worth emphasizing that this information can help policy makers to calibrate the strength of their policy interventions. Additionally, it can be used by private investors to be pondered when optimizing their portfolios at the global scale.

[4] A detail risk assessment using the LAMI is not presented here but is available upon request.

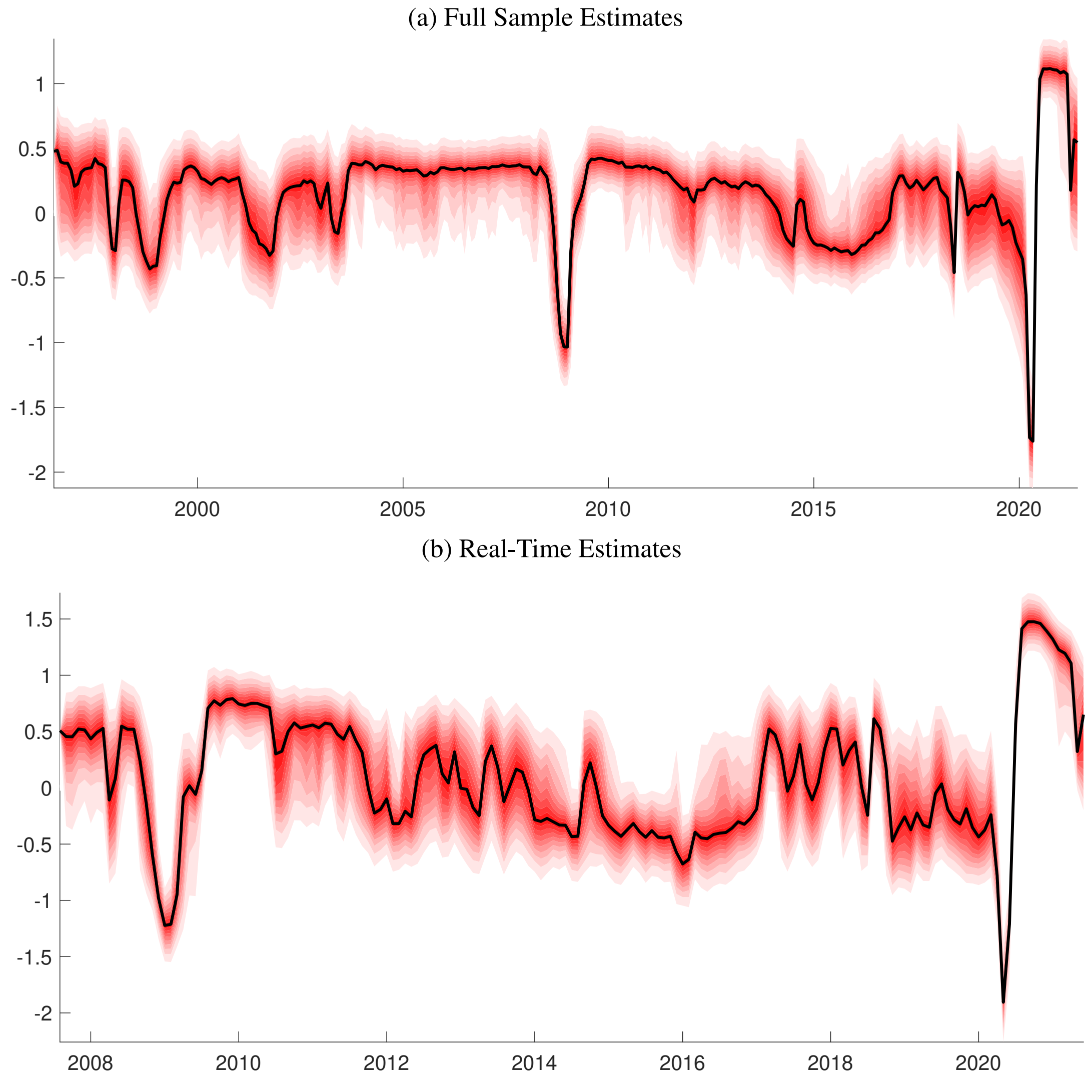

Figure 3: *Latin American Momentum Index (LAMI)*

Note: Chart A and Chart B plot the full sample (1996:06-2021:05) and real-time (2007:07-2021:05) estimates of the LAMI, respectively. In both charts the solid black line indicates the median of the posterior density, while the red area makes reference to the entire density.

4. U.S. financial conditions and LATAM momentum

Latin America has been typically vulnerable to U.S. shocks, whether real or financial. For example, Canova (2005) and Albagli et al. (2016) show that U.S. monetary shocks have significant effects over LATAM's business cycles. Henceforth, a natural application of our proposed measures is to study how changes in U.S. financial conditions impact over the growth momentum of the region. To illustrate this relationship, Figure 4 plots the LAMI, described preciously, together with the U.S. Financial Conditions Index, which is produced by the Federal Reserve Board of Chicago and built as a weighted average of more than a hundred variables of the financial activity, including the Fed and Treasury yield rates at different maturities. An increase in this index indicates that the U.S. financial conditions become tighter. At first glance, the figure shows a negative contemporaneous relation between both indices.

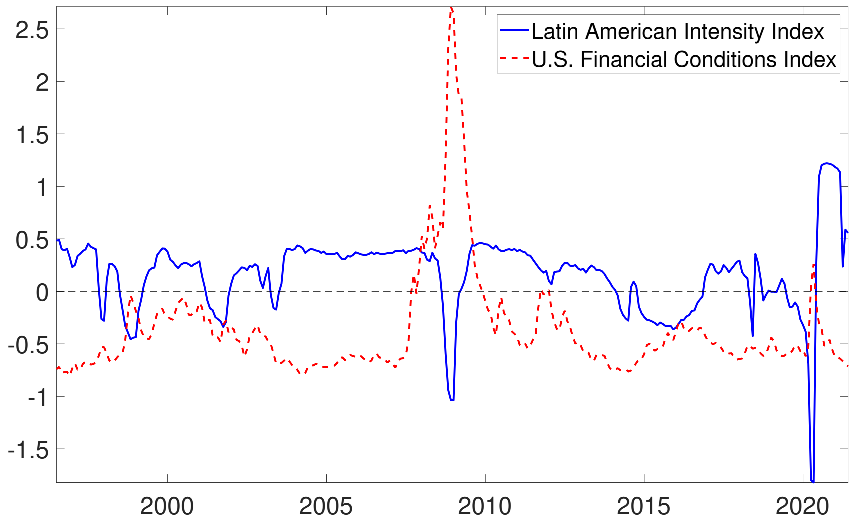

Figure 4: *Latin American Momentum Index and U.S. Financial Conditions Index*

Note. The solid blue line plots the LAMI, and the dashed red line plots the U.S. Financial Conditions Index (NFCI), constructed by the Federal Reserve Bank of Chicago.

We proceed then to estimate the evolving size and duration of the impact of the U.S. financial conditions over the Latin American economic momentum. In doing so, let $LAMI_t^{(l)}$ be the l-th draw of the Latin American Momentum Index at time t, and FCI_t be the U.S. National Financial Conditions Index. Then, in order to account for the uncertainty associated with the dependent variable, we estimate the following time-varying parameter regression,

$$LAMI_t^{(l)} = \alpha_t^{(l)} + \beta_t^{(l)} FCI_t + \gamma_t^{(l)} C19_t + e_t^{(l)}, \tag{8}$$

for $l = 1, ..., L$, with L being the number of iterations used to estimate each model in a Bayesian fashion, where $e_t^{(l)} \sim N(0, \sigma_e^{(l)})$, $\alpha_t^{(l)}$ denotes the intercept that controls for the nonlinearities embedded in the dynamics of real activity and $\beta_t^{(l)}$ is the effect of U.S. financial conditions over LATAM's economic momentum. Since the large fall in activity during the early 2020 was not induced by fundamentals but due to an exogenous factor, the COVID-19 pandemics, an additional control is introduced in the regression through information on mobility.[5] Particularly, we define the following control variable,

$$C19_t = \begin{cases} 0 & \text{If } t \leq \tau \\ mobility_t & \text{If } t > \tau \end{cases} \tag{9}$$

[5]Recent works by Chetty et al. (2020), Fernández-Villaverde and Jones (2020), and Lewis et al. (2021) provide convincing evidence that mobility measures carry valuable information about the rapid economic decline in the early stages of the COVID-19 crisis.

with τ referring to February 2020, that is aimed to capture the part of the decline in LATAM's momentum during 2020 that should not be attributed to underlying economic factors, but to the pandemics. The variable $mobility_t$ makes reference to an average of the mobility indices associated with the countries under consideration. In addition, to account for nonlinearities embedded in Equation (8), we allow the intercept and all slope parameters to evolve according to random walk dynamics,

$$\alpha_t^{(l)} = \alpha_{t-1}^{(l)} + v_t^{(l)} \quad (10)$$

$$\beta_t^{(l)} = \beta_{t-1}^{(l)} + \nu_t^{(l)} \quad (11)$$

$$\gamma_t^{(l)} = \gamma_{t-1}^{(l)} + u_t^{(l)} \quad (12)$$

where $v_t^{(l)} \sim N(0, \sigma_v^{(l)})$, $\nu_t^{(l)} \sim N(0, \sigma_\nu^{(l)})$ and $u_t^{(l)} \sim N(0, \sigma_u^{(l)})$.[6]

Figure 5 plots the estimated slope coefficient, β_t, showing a significantly negative impact during three specific periods when tighter U.S. financial conditions were associated with smaller medium-term growth of Latin American economic activity. The first one corresponds to the late 1990s and early 2000s, which coincides with a tightening in U.S. monetary policy, also reflected in a prolonged period of worse overall financial conditions in U.S. The second period refers to 2009, the middle of the "Great Recession", when U.S. financial conditions exhibited the tightest historical values. Although, note that during 2009 the effect of U.S. on LATAM was of a smaller magnitude, shorter duration and smaller uncertainty, than during late 1990s and early 2000s. The third period corresponds to the second half of 2020. Although U.S. financial conditions deteriorated only temporarily during this period, they had a significant impact on LATAM's economic momentum. This feature possess an important warning for LATAM's policy makers due to the expected monetary policy normalization process associated with the U.S. economy once the Quantitative Easing cycle is over.

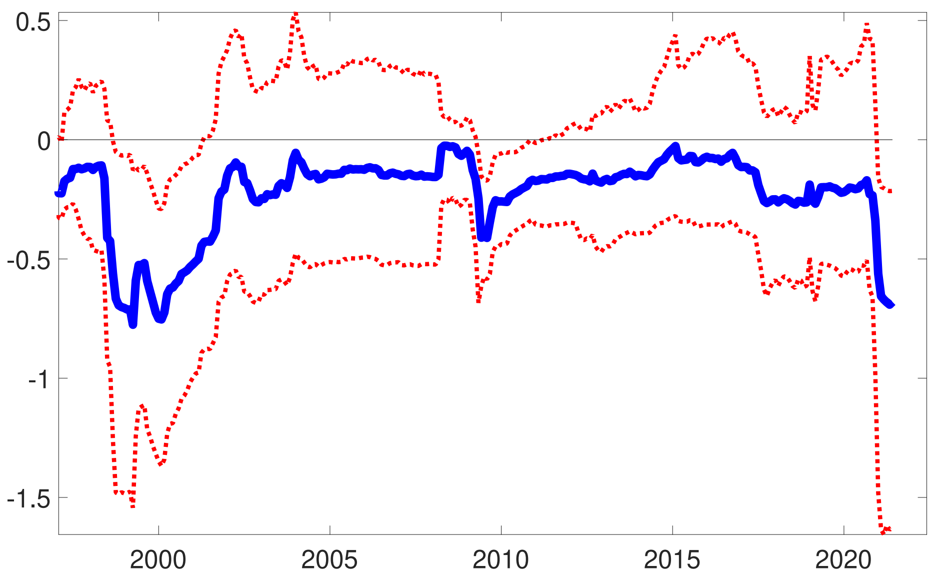

Figure 5: Effect of U.S. Financial Conditions on Latin American Momentum

Note: The solid blue line plots the contemporaneous correlation between U.S. financial conditions and the Latin American Momentum Index. The dotted red lines make reference to the percentiles 16 and 84 of the corresponding posterior density.

Overall, these results illustrate how financial conditions in the U.S. have had a detrimental and

[6] For each draw l of the LAMI's posterior density, we estimate a time-varying parameter regression. The Kalman filter is used to infer the latent states from a state-space representation formed by Equation (8), as measurement, and equations (10)-(12), as transition. The parameters are estimated by maximum likelihood.

significant effect on the medium-term growth of the Latin American economy. To the best of our knowledge, this paper is the first documenting these types of effect based on what can be considered as high frequency, i.e. monthly, data for Latin America.[7]

5. Conclusions

In this paper, we provide two new indices to measure the Latin American business cycle from different, but complementary, angles that have not been previously exploited in the region. We employ a novel technique, which is particularly useful since the exceptional magnitudes of the fall and rebound in the Latin American economy induced by the COVID-19 pandemics, to estimate probabilities of recessions and expansions that consider the uniqueness of each phase of the business cycle.

To measure the state of the region's economy in real time, we present the Latin American Weakness Index (LAWI). The LAWI quantifies the fraction of the LATAM's economy facing a recession at each point in time. A variance decomposition of this index allows to identify which countries contributed more to the recessions (and expansions) affecting the region during the last decades.

Next, to measure the deepness (buoyancy) of an economic recession (expansion) in Latin America, we present the Latin American Momentum Index (LAMI), that quantifies the momentum embedded in observed short-term fluctuations of monthly real activity growth. The estimates identify three types of LATAM recessions in terms of deepness, "small", "large" and "very large". Instead, LATAM expansionary episodes can be categorized into "normal" and "abnormal".

Lastly, we present an empirical application where we illustrate additional uses of our indices by studying the evolving effect of U.S. financial conditions on the medium-term growth of the Latin American economy. The use of the proposed measures help to quantify the size and persistence of the negative effects that tighter U.S. financial conditions have on the LATAM's business cycle.

[7] It is also important to acknowledged that this empirical application is based on a contemporaneous correlation of observed variables, and not on the effect of structural shocks. Further extensions can be also considered by accounting for the identification of underlying structural shocks.

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A. Data

The description, sources and data transformation is presented in Table 1. The synchronization (Sync) column shows the number of weeks elapsed between the end of the quarter or month of publication and the point at which they are actually published.

Sources of information.

- INDEC: Instituto Nacional de Estadística y Censos de la República Argentina.
- INE: Instituto Nacional de Estadisticas.
- IBGE: Instituto Brasileiro de Geografia e Estatistica.
- BCB: Banco Central do Brasil.
- BCC: Banco Central de Chile.
- CCHC: Cámara Chilena de la Construcción.
- DANE: Departamento Administrativo Nacional de Estadísticas.
- BR: Banco de la República.
- BCE: Banco Central del Ecuador.
- INEC: Instituto Nacional de Estadística y Censos.
- INEGI: Instituto Nacional de Estadística y Geografía.
- INEI: Instituto Nacional de Estadística e Informática.

Table 1: *List of variables for each country*

Variable	Source	Frequency	First observation	Sync	SA*	BP**
Argentina						
Real GDP	INDEC	Quarterly	2004:I	Week 10	-	-
Imports of goods and services	INDEC	Monthly	1990:1	Week 3	-	-
Exports of goods and services	INDEC	Monthly	1990:1	Week 3	-	-
Construction activity index	INDEC	Monthly	1993:1	Week 5	✓	✓
Monthly economic activity index	INDEC	Monthly	2004:1	Week 5	✓	✓
Bolivia						
Real GDP	INE	Quarterly	1990:I	Week 12	✓	-
Imports of goods and services	INE	Monthly	1992:1	Week 4	✓	-
Exports of goods and services	INE	Monthly	1992:1	Week 4	✓	-
Total cement production	INE	Monthly	1991:1	Week 4	✓	-
Global economic activity index	INE	Monthly	2008:1	Week 5	✓	-
Brazil						
Real GDP	IBGE	Quarterly	1996:I	Week 10	-	-
Imports of goods and services	BCB	Monthly	1995:1	Week 1	✓	-
Exports of goods and services	BCB	Monthly	1995:1	Week 1	✓	-
Industrial production index	IBGE	Monthly	2002:1	Week 4	-	-
Retail trade sales volume	IBGE	Monthly	2000:1	Week 5	✓	-
Monthly economic activity index	Bloomberg	Monthly	2003:1	Week 5	-	-
Chile						
Real GDP	BCC	Quarterly	1996:I	Week 10	-	✓
Imports of goods and services	BCC	Monthly	2003:1	Week 1	✓	-
Exports of goods and services	BCC	Monthly	2003:1	Week 1	✓	-
Manufacturing production Index	INE	Monthly	1991:1	Week 4	-	-
IMACON	CCHC	Monthly	1990:1	Week 4	-	-
Monthly economic activity index	Bloomberg	Monthly	2008:1	Week 4	-	-
Colombia						
Real GDP	DANE	Quarterly	1994:I	Week 6	-	✓
Imports of goods and services	BR	Monthly	1990:1	Week 4	✓	-
Exports of goods and services	BR	Monthly	1990:1	Week 4	✓	-
Manufacturing production Index	DANE	Monthly	2001:1	Week 6	-	-
Building permits index	Bloomberg	Monthly	2009:1	Week 6	-	-
Monthly economic activity index	DANE	Monthly	2005:1	Week 6	-	-
Ecuador						
Real GDP	BCE	Quarterly	2000:I	Week 10	-	-
Imports of goods and services	Bloomberg	Monthly	1990:1	Week 6	✓	-
Exports of goods and services	Bloomberg	Monthly	1990:1	Week 6	✓	-
Global business confidence index	BCE	Monthly	2007:5	Week 4	✓	-
Recorded activity level index	INEC	Monthly	2003:1	Week 7	✓	-
Mexico						
Real GDP	INEGI	Quarterly	1993:I	Week 10	-	-
Imports of goods and services	INEGI	Monthly	1993:1	Week 5	✓	-
Exports of goods and services	INEGI	Monthly	1993:1	Week 5	✓	-
Industrial Activity Indicator	INEGI	Monthly	1993:1	Week 5	-	-
Private Consumption Indicator	INEGI	Monthly	1993:1	Week 5	-	-
Retail trade sales index	Bloomberg	Monthly	2008:1	Week 7	-	-
Economic activity index	INEGI	Monthly	1993:1	Week 7	-	-
Peru						
Real GDP	INEI	Quarterly	2007:I	Week 9	✓	-
Imports of goods and services	FRED St.Louis	Monthly	1990:2	Week 6	✓	-
Exports of goods and services	FRED St.Louis	Monthly	1990:2	Week 6	✓	-
Building permits index	Bloomberg	Monthly	2001:1	NA	✓	-
Economic activity index	Bloomberg	Monthly	2007:1	Week 7	-	-

* The variable has been seasonal adjusted with the U.S. Census Bureau X-13 seasonal adjustment tools.
** The same time series but with a different statistical basis has been backpolated.
Note: All the variables are expressed in growth rates and standardized prior to estimate the model.

B. Additional Details on the Model and Estimation

Let vectors μ_0 and μ_1 record the values of recession- and expansion-specific means applicable at $t = 1, ..., T$. We can write the two mean processes as follows:

$$\mu_{0,t} = (1 - d_{0,t})\mu_{0,t-1} + d_{0,t}\mu_{0,\tau_0}, \tag{13}$$

$$\mu_{1,t} = (1 - d_{1,t})\mu_{1,t-1} + d_{1,t}\mu_{1,\tau_1}, \tag{14}$$

where the indicator variables $d_{0,t}$ and $d_{1,t}$ are defined as

$$d_{0,t} = \begin{cases} 1 \text{ when } s_t = 0, \ s_{t-1} = 1 \\ 0 \text{ otherwise} \end{cases}, \qquad d_{1,t} = \begin{cases} 1 \text{ when } s_t = 1, \ s_{t-1} = 0 \\ 0 \text{ otherwise} \end{cases}$$

The time domain $t = 1, ..., T$ is partitioned into N_0 recessionary and N_1 expansionary episodes, where a recession is followed by an expansion, which, in turn, must be followed by another recession. The mean μ_{0,τ_0} represents the expected value of the factor f_t during the τ_0-th recession, $\tau_0 = 1, ..., N_0$, and μ_{1,τ_1} corresponds to the τ_1-th expansion, $\tau_1 = 1, ..., N_1$. Accordingly, regime-dependent means can be specified as follows:

$$\mu_{0,\tau_0} \sim \mathcal{N}(\bar{\mu}_{0,\tau_0}, \sigma^2_{\mu_{0,\tau_0}}) \text{ i.i.d.,} \tag{15}$$

$$\mu_{1,\tau_1} \sim \mathcal{N}(\bar{\mu}_{1,\tau_1}, \sigma^2_{\mu_{1,\tau_1}}) \text{ i.i.d.} \tag{16}$$

That is, each recessionary and expansionary episode has its own unique mean of the common factor, which is independent of other episodes.[8] For example, suppose that period t corresponds to a τ_0-th recession, so that $s_t = 0$. In this case, the common factor is expected to equal the recession-specific mean μ_{0,τ_0}. The expansion-specific mean μ_{1,τ_1} has no effect: we assume that it remains the same as during the τ_1-th expansion that was right before the τ_0-th recession. When the τ_0-th recession ends, the recession-specific mean μ_{0,τ_0} becomes ineffective and a new expansion-specific mean μ_{1,τ_1+1} determines the expected value of the common factor.

To give an example, suppose that the economy begins with a recession. Then, for $t = 1, ..., T$, the following values of μ_{0,τ_0} and μ_{1,τ_1} would be applicable:

$$
\begin{array}{cc}
t & s_t \\
1 & 0 \\
2 & \vdots \\
\vdots & 0 \\
 & 1 \\
 & \vdots \\
 & 1 \\
 & 0 \\
 & \vdots \\
 & 0 \\
 & 1 \\
 & \vdots \\
\vdots & 1 \\
T & \vdots
\end{array}
\quad
\begin{array}{c}
\mu_{0,t} \\
\underbrace{\begin{bmatrix}
\mu_{0,\tau_0=1} \\ \vdots \\ \mu_{0,\tau_0=1} \\ \mu_{0,\tau_0=1} \\ \vdots \\ \mu_{0,\tau_0=1} \\ \mu_{0,\tau_0=2} \\ \vdots \\ \mu_{0,\tau_0=2} \\ \mu_{0,\tau_0=2} \\ \vdots \\ \mu_{0,\tau_0=2} \\ \vdots
\end{bmatrix}}_{\mu_0}
\end{array}
\quad
\begin{array}{c}
\mu_{1,t} \\
\underbrace{\begin{bmatrix}
\mu_{1,\tau_1=0} \\ \vdots \\ \mu_{1,\tau_1=0} \\ \mu_{1,\tau_1=1} \\ \vdots \\ \mu_{1,\tau_1=1} \\ \mu_{1,\tau_1=1} \\ \vdots \\ \mu_{1,\tau_1=1} \\ \mu_{1,\tau_1=2} \\ \vdots \\ \mu_{1,\tau_1=2} \\ \vdots
\end{bmatrix}}_{\mu_1}
\end{array}
\quad
\begin{array}{l}
\left.\begin{array}{l} \\ \\ \\ \end{array}\right\} \text{1st recession, } \tau_0 = 1 \\
\left.\begin{array}{l} \\ \\ \\ \end{array}\right\} \text{1st expansion, } \tau_1 = 1 \\
\left.\begin{array}{l} \\ \\ \\ \end{array}\right\} \text{2nd recession, } \tau_0 = 2 \\
\left.\begin{array}{l} \\ \\ \\ \end{array}\right\} \text{2nd expansion, } \tau_1 = 2 \\
\qquad \vdots \\
\\
\end{array}
$$

Note that, because the first episode in the data is a recession, we use $\mu_{1,\tau_1=0}$ for the initial values of the expansionary mean (which have no effect during the first recession).[9]

In order to extract the common factor, the non-linear dynamic factor model is cast in a state-space form. Let vector $y_t = [y^q_t, y^m_{1,t}, ..., y^m_{M,t}]'$ contain the growth rates for the quarterly variable and M monthly variables included into the data set. Assuming that all the variables in vector y_t are observed

[8] For identification purposes, we impose an expectation that the common factor should be lower during a recession: $\mu_0 < \mu_1$.

[9] In principle, $\mu_{1,\tau_1=0}$, that is, the counterfactual growth rate during the expansion prior to the beginning of the sample, can be also treated as a parameter to be estimated. Nevertheless, for the empirical application, we assume $\mu_{1,\tau_1=0} = 0$ to reduce estimation uncertainty.

in period t, they can be related to their unobserved idiosyncratic components and the common factor as follows:

$$y_t = \mathbf{H} z_t + \eta_t, \quad \eta_t \sim \mathcal{N}(0, \mathbf{R}). \tag{17}$$

In the observation equation above, vector z_t contains the unobserved common factor and the idiosyncratic components. More generally, in periods when some of the observations are missing, the observation equation can be cast without the rows that correspond to the missing observations:

$$y_t^* = \mathbf{H}_t z_t + \eta_t^*, \quad \eta_t^* \sim \mathcal{N}(0, \mathbf{R}_t), \tag{18}$$

where $\mathbf{H}_t$ is obtained by taking $\mathbf{H}$ and eliminating the rows that correspond to the missing variables, and the matrix $\mathbf{R}_t$ is obtained by eliminating the corresponding rows and columns from matrix $\mathbf{R}$.

To complement the observation equation and complete the description of the model, let the first element of the unobserved vector z_t be the common factor. Then, the dynamic behavior of the common factor, f_t, and the idiosyncratic components, $\{u_{i,t}\}^i$, can be summarized with the following transition equation:

$$z_t = \boldsymbol{\mu}_t + \mathbf{F} z_{t-1} + \varepsilon_t, \quad \varepsilon_t \sim \mathcal{N}(0, \mathbf{Q}), \tag{19}$$

where $\boldsymbol{\mu}_t = (\mu_t, 0, ..., 0)'$, $\mu_t = s_t \mu_{1,t} + (1 - s_t)\mu_{0,t}$, and the time-varying means $\mu_{0,t}$ and $\mu_{1,t}$ are defined as in equations (13) and (14), respectively. Therefore, $\mu_t = \mu_{1,\tau_1}$ if period t corresponds to the τ_1-th expansion, and $\mu_t = \mu_{0,\tau_0}$ if period t corresponds to the τ_0-th recession.

We employ Bayesian methods to produce inferences on both its parameters and the values of the latent variables given the embedded nonlinearities. Let $Y = \{y_t\}_{t=1}^T$ contain all the available data; similarly, let $Z = \{z_t\}_{t=1}^T$. Let $S = \{s_t\}_{t=1}^T$ be the collection of the latent regimes, and let $\mu = \{\mu_t\}_{t=1}^T$ contain the information on the regime-dependent means associated with expansionary and recessionary episodes. All the parameters that specify the model are collected in $\theta = \left\{p, q, \sigma_f^2, \{\gamma_i\}, \{\psi_{i,m}\}, \{\sigma_i^2\}\right\}$. Given data Y and prior distributions for the parameters contained in vector θ, we rely on the following iterative procedure to generate draws of $\{Z^l, S^l, \theta^l, \mu^l\}_{l=1}^L$, which constitute the posterior distribution of Z, S, θ, and μ:

1. Given Y, S^{l-1}, μ^{l-1}, and θ^{l-1}, generate Z^l from $P(Z|Y, S, \theta)$. This step follows Appendix 1 of Carter and Kohn (1994) by using the state space representation in Equations (18)-(19).
2. Given Z^l, μ^{l-1} and θ^{l-1}, generate S^l from $P(S|Z, \theta)$. This step is based on the law of motion of the common factor and follows Appendix 2 of Carter and Kohn (1994).
3. Given Y, Z^l, S^l, and μ^l, simulate θ^l using the Gibbs sampler and the standard conjugate prior distributions.
4. Given Z^l, S^l, and θ^{l-1}, generate μ^l. The key feature that allows the model to accurately infer all types of recessions and expansions, independently on whether they are of mild, severe, or extremely severe magnitude, is the flexibility when sampling the regime-dependent means defined in equations (13) and (14). Accordingly, we apply the partition of the time domain into the recessionary, $\tau_0 = 1, ..., N_0$, and expansionary, $\tau_1 = 1, ..., N_1$, episodes as dictated by the current realization of the state indicator S^l, and treat each episode separately. Then, for each individual episode, we sample its corresponding common factor growth rate mean by only using the corresponding information, that is, $\{f_t\}_{t\in\tau_0}$ and $\{f_t\}_{t\in\tau_1}$. In doing so, we use normal distributions as priors, which are conjugate with the posterior.

The above four steps are iterated for $l = 1, ..., L$, with $L = 10,000$. The posterior densities of all the elements of the model are constructed with the collection of all the generated draws.

Step 3 of the algorithm needs to be described in more detail. let us recall that $Y = \{y_t\}_{t=0}^{T}$ collects the observed data, while $Z^l = \{z_t^l\}_{t=0}^{T}$, and $S^l = \{s_t^l\}_{t=0}^{T}$ constitute the l-th draw of the latent continuous and discrete variables, respectively, and θ^l is the l-th draw of the parameter vector. Accordingly, conditional on Y, S^l and z^l, the l-th draw of θ^l is obtained with the following procedure:

- Our aim is to be as flexible as possible when sampling the regime-dependent means, μ_{0,τ_i} and μ_{1,τ_i}. This is because flexibility is the key feature that allows our framework to accurately infer all types of recession and expansion, independently of whether they are of mild, severe, or extremely severe magnitude. Therefore, we treat the mean growth of the common factor, f_t, associated with each specific phase of the business cycle in a personalized manner, by sampling it conditional only on the information of f_t associated with the corresponding time interval, which is dictated by s_t. The prior distribution for both recessionary and expansionary means are assumed to be normal, $\mu_{0,\tau_i} \sim \mathcal{N}(a_0, V_0)$ and $\mu_{1,\tau_i} \sim \mathcal{N}(a_1, V_1)$. Accordingly, by letting $Y_{0,\tau_i}^* = \{f_t \mid s_t = 0\}_{t\in\tau_i}$ and $Y_{1,\tau_i}^* = \{f_t \mid s_t = 1\}_{t\in\tau_i}$ the regime-dependent means can be drawn from the normal posterior distribution, $\mathcal{N}(\bar{a}_{l,\tau_i}, \bar{V}_{l,\tau_i})$ defined by

$$\bar{V}_{l,\tau_i} = \left(V_l^{-1} + \left(X_{l,\tau_i}^*\right)' X_{l,\tau_i}^*\right)^{-1};$$

$$\bar{a}_{l,\tau_i} = V_l \left(V_l^{-1} a + \left(X_{l,\tau_i}^*\right)' Y_{l,\tau_i}^*\right),$$

  where X_{l,τ_i}^*, for $l = \{0, 1\}$.

- The factor loadings γ_j are assumed to be normally distributed $\gamma_j \sim \mathcal{N}(a, V)$. Letting $\tilde{y}_{j,t}$ and $\tilde{f}_{j,t}$ be defined as:

$$\tilde{y}_{j,t} = y_{j,t} - \psi_{j,1}^i y_{j,t-1} - ... - \psi_{j,P}^i y_{j,t-P};$$

$$\tilde{f}_{j,t}^i = f_t^i - \psi_{j,1}^i f_{t-1}^i - ... - \psi_{j,P}^i f_{t-P}^i,$$

  it follows that,

$$\tilde{y}_{j,t} = \gamma_j \tilde{f}_{j,t}^i + e_{j,t}, e_{j,t} \sim \mathcal{N}(0, \sigma_j^2).$$

  Using expression above, we can find the posterior for the factor loading to be normally distributed as well: $\gamma_j \sim \mathcal{N}(\bar{a}_j, \bar{V}_j)$, such that

$$\bar{V}_j = \left(V^{-1} + \left(\tilde{X}_j\right)' \tilde{X}_j\right)^{-1};$$

$$\bar{a}_j = \bar{V}\left(V^{-1} a + \left(\tilde{X}_j\right)' \tilde{Y}_j\right),$$

  where $\tilde{X}_j$ and $\tilde{Y}_j$ are vectors with elements $\left\{\tilde{f}_{j,t}\right\}$ and $\{\tilde{y}_{j,t}\}$ defined above. Then, the factor loadings $\left\{\gamma_j^{i+1}\right\}$ are drawn from these posteriors.

- We assume that the individual component of the only quarterly variable in our model is a white noise, which makes it simpler to compute the posterior density, due to the monthly missing observations in a variable at the quarterly frequency. In particular, for the individual component of GDP growth, we have that,

$$u_{1,t} = e_{1,t}, e_{1,t} \sim \mathcal{N}(0, \sigma_1^2).$$

Then, we specify the inverse-gamma prior $\sigma_1^2 \sim \mathcal{IG}(a, b)$, which conjugates with the inverse-gamma posterior $\mathcal{IG}(\tilde{a}, \tilde{b})$, such that,

$$\bar{a} = a + \frac{T}{2}, \bar{b} = \frac{1}{b + \frac{\sum\left(y_{1,t}^i\right)^2}{2}}.$$

Then, the variance $\left(\sigma_1^{i+1}\right)^2$ is simulated from this posterior.

- Define $Y_j = (y_{j,1}, ..., y_{j,T})$ to be the vector collecting the observations of a monthly variable j. let X_j be the $T \times P$ matrix recording the P lags of the variable $y_{j,t}$. For the AR coefficients of each monthly variable individual component $\psi_j = (\psi_{j,1}, ..., \psi_{j,P})'$, we assume the same normal prior $\psi_j \sim \mathcal{N}(0, V)$, then the posterior is also normal $\mathcal{N}(\bar{a}_j, \bar{V}_j)$, but different for each j, such that

$$\bar{V}_j = \left(V^{-1}a + \frac{X_j' X_j}{\left(\sigma_j^i\right)^2}\right)^{-1};$$

$$\bar{V}_j = \bar{V}_j\left(V^{-1}a + \frac{X_j' Y_j}{\left(\sigma_j^i\right)^2}\right)^{-1},$$

We simulate ψ_j^{i+1} from this posterior. Finally, to simulate σ_j^{i+1}, we assume inverse-gamma prior: for each j, $\sigma_j^2 \sim \mathcal{IG}(a, b)$. Let Ψ_j^{i+1} be the following $P \times P$ matrix

$$\Psi_j^{i+1} = \begin{bmatrix} \psi_{j,1}^{i+1} & \cdots & \psi_{j,P-1}^{i+1} & \psi_{j,P}^{i+1} \\ 1 & \cdots & 0 & 0 \\ \vdots & \ddots & \vdots & \vdots \\ 0 & \cdots & 1 & 0 \end{bmatrix}$$

Then, we can express the posterior of σ_j^2 as an inverse-gamma distribution as well, $\mathcal{IG}(\bar{a}, \bar{b})$, such that

$$\bar{a} = a + \frac{T}{2}; \bar{b} = \left(b + \frac{\left(Y_j - X_j \Psi_j^{i+1}\right)'\left(Y_j - X_j \Psi_j^{i+1}\right)}{2}\right)^{-1}$$

We simulate AR coefficients Ψ_j^{i+1} from these posteriors [10].

- For S^{i+1}, let n_{11}^{i+1} count the number of times that indicator s_t^{i+1} has remained at one: $n_{11}^{i+1} = \sum_{t=2}^{T} 1\left(s_t^{i+1} = s_{t-1}^{i+1} = 1\right)$. Similarly, let n_{00}^{i+1} count the number of times it has remained at zero, and n_{10}^{i+1} and n_{01}^{i+1} count the number of times it has switched the value. Then, assuming the same beta prior distribution $\beta(a, b)$ for both p and q, the posterior distribution is of the same shape $\beta(\bar{a}, \bar{b})$. In the case of p, the probability of remaining in a normal episode (when $s_t = 0$), is updated with $\bar{a} = a + n_{00}$ and $\bar{b} = b + n_{01}$. For q, the updates are $\bar{a} = a + n_{11}$ and $\bar{b} = b + n_{10}$.

[10] The variance of the factor σ_f^2 is set equal to one for identification purposes (Bai and Wang, 2015).

Table 2: *Moments of the prior distributions of the estimated model parameters*

Parameter	Meaning	Distribution	a	b
	Common Factor			
p	Probability of staying in a expansion	$\beta(a, b)$	90	10
q	Probability of staying in a recession	$\beta(a, b)$	90	10
μ_0	Mean growth rate during expansions*	$\mathcal{N}(a, b)$	2	1
μ_1	Mean growth rate during recessions*	$\mathcal{N}(a, b)$	-2	1
	Individual components			
γ_i	factor loading for ind. variable i^+	$\mathcal{N}(a, b)$	0	1
$\psi_{i,j}$	AR coefficient for ind. var. i-lag j	$\mathcal{N}(a, b)$	0	1
σ_2^i	Variance of shock to ind. variable i	$\mathcal{IG}(a, b)$	10	0.1(a-1)

* Mean growth rates might be different among countries.