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Latin American Falls, Rebounds and Tail Risks*

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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, (ii) the underlying momentum embedded in short-term fluctuations of real activity, and (iii) the quantification of macroeconomic tail risks. 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 Classification Code: E32, C22, E27.

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Caídas, repuntes y riesgos de cola en América Latina

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Resumen

En este documento se proponen diferentes medidas para estimar el ciclo económico de América latina, con las que se permite observar la profundidad de las recesiones y la fuerza de las expansiones de la economía de la región en tiempo real. Estas medidas se construyen con los datos observados de las economías más grandes de latinoamérica y tienen en cuenta diferentes características de la actividad real, capturando los comovimientos, no linealidades y asimetrías que caracterizan la actividad económica de la región, al tiempo que son robustas frente a choques sin precedentes como el de la pandemia COVID 19. Las medidas propuestas proporcionan información sobre; (i) el estado de la economía regional, (ii) el momentum de la actividad económica en el corto plazo, y (iii) la cuantificación de los riesgos de cola macroeconómicos. Usando las medidas propuestas también evaluamos los efectos que tienen las condiciones financieras de EE.UU sobre la economía latinoamericana.

Palabras Clave: Ciclos Económicos, Modelos de Factores, No linealidad, América Latina.

Clasificación JEL: E32, C22, E27.

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 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]

[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 by using information on payments made with electronic transfers and cheques 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 provide nowcasts of monthly industrial production in selected Latin American countries by relying on

In this paper, we propose new measurements for both country-specific and 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 of the region 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. We then summarize these country-specific inferences into four indices that provide an accurate and comprehensive picture of the state of the LATAM economy in real time.

The first of these indices 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

MIDAS regressions.

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.

Due to the mounting risks induced by recent unprecedented global economic events, assessments on the distributional properties of macroeconomic activity are crucial for policy makers in the evaluation of different scenarios. Therefore, we propose a novel characterization of macroeconomic tails risks in the Latin American economy. In doing so, we rely on higher order moments associated with the time-varying empirical distribution of the LAMI, and provide real-time assessments on (i) the direction of macroeconomic tail risks in the region, through the LAMI's skewness, and (ii) how prone is LATAM's economic activity to exhibit extreme values, with the LAMI's kurtosis. Based on this information, we are able to characterize four different types of risks through which the LATAM's business cycle transitions: from the "best" to the "worst" scenario, and also to identify the time periods associated to each of them.

The fourth, and last, measure is referred to as the Latin American Activity Index (LACI) and calculates the monthly short-term fluctuations in real activity of LATAM. In particular, it provides real-time monthly inferences on, a counterfactual, quarterly GDP growth of the region. The LACI suggests that LATAM experienced its lowest quarterly growth in May 2020, with -14%, and its maximum quarterly growth in September 2020, with 10%. These figures represent the bottom and top of the LATAM economy during the COVID-19 crisis, respectively. We show that the LACI follows with accurate precision the World Bank's real GDP growth of LATAM. Hence, this index is suitable to perform out-of-sample forecasts of aggregate activity for the region.

These four types of 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 country-specific and 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.

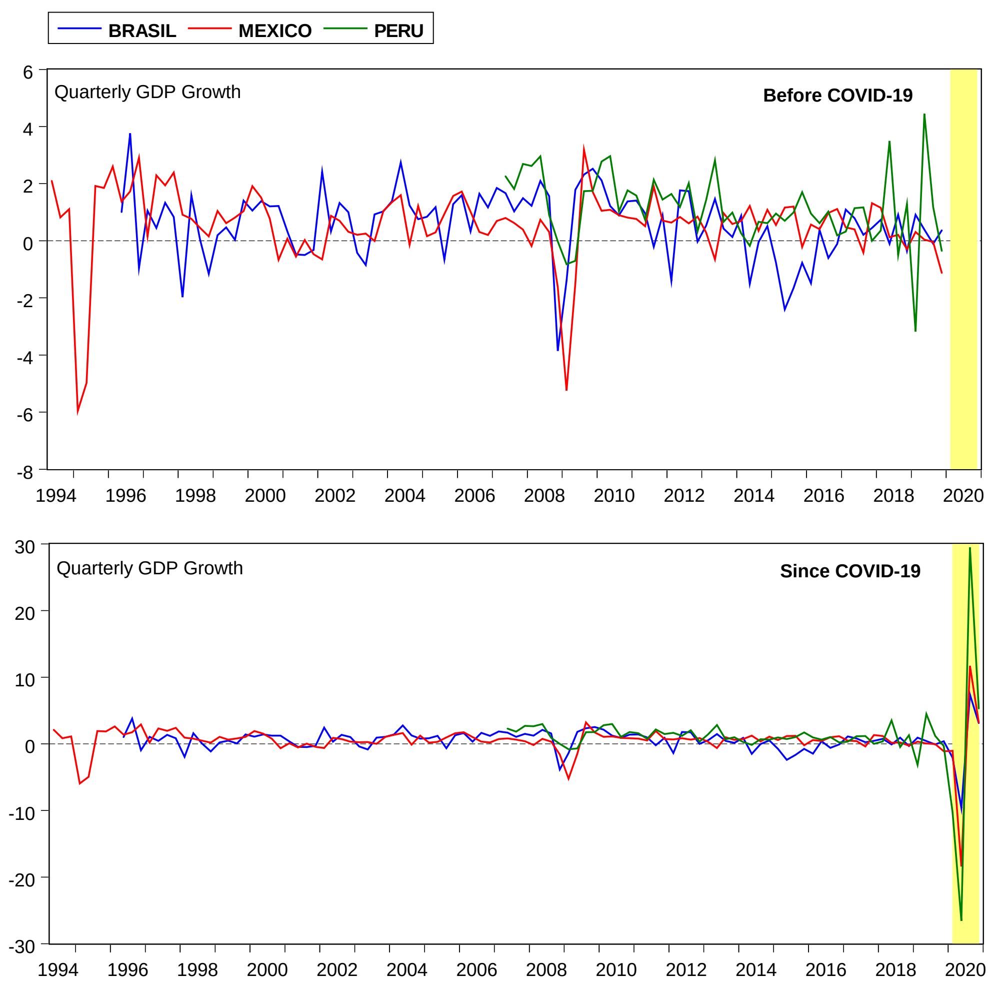
Lastly, we present an empirical application that illustrates one possible alternative use of the proposed indices, other than monitoring purposes. In particular, we explore how U.S. financial conditions influence medium-term economic fluctuations in the LATAM economy. This analysis is meaningful in that 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.

The rest of the paper is organized as follows. Section 2 highlights the advantages of the empirical methodology employed in this paper in comparison with previous frameworks typically used in the literature. Section 3 presents the country-specific results. Section 4 introduces the new indices for the measurement of LATAM's business cycles, which constitute the main contribution of our work. Section 5 presents the empirical application of the proposed indices regarding how U.S. financial conditions affect LATAM economy. Finally, section 6 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

[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. Accordingly, 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.

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 let the common factor to exhibit 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 could 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 would provide 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, therefore, where it becomes more difficult to extract, from the data, precise and prompt assessments about the direction where the economy is heading to.[3]

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

[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.

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, the framework of Leiva-León et al. (2021) is different from that of Eo and Kim (2016) in that the latter is based on a univariate model, for GDP only, that restricts the underlying regime-dependent means to exhibit time persistence through random walk processes. Instead, the means defined in Equation (4) are not restricted to exhibit any time persistence, that is, $cov(\mu_{\iota,\tau_\iota}, \mu_{\iota,\tau_\iota - j}) = 0$, $\forall j$, for $\iota = 0, 1$. This feature is of high importance when confronting the model to economies that exhibit sequences of expansions and recessions of either small, large or extremely magnitudes, such as the ones 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 Real momentum in LATAM economies

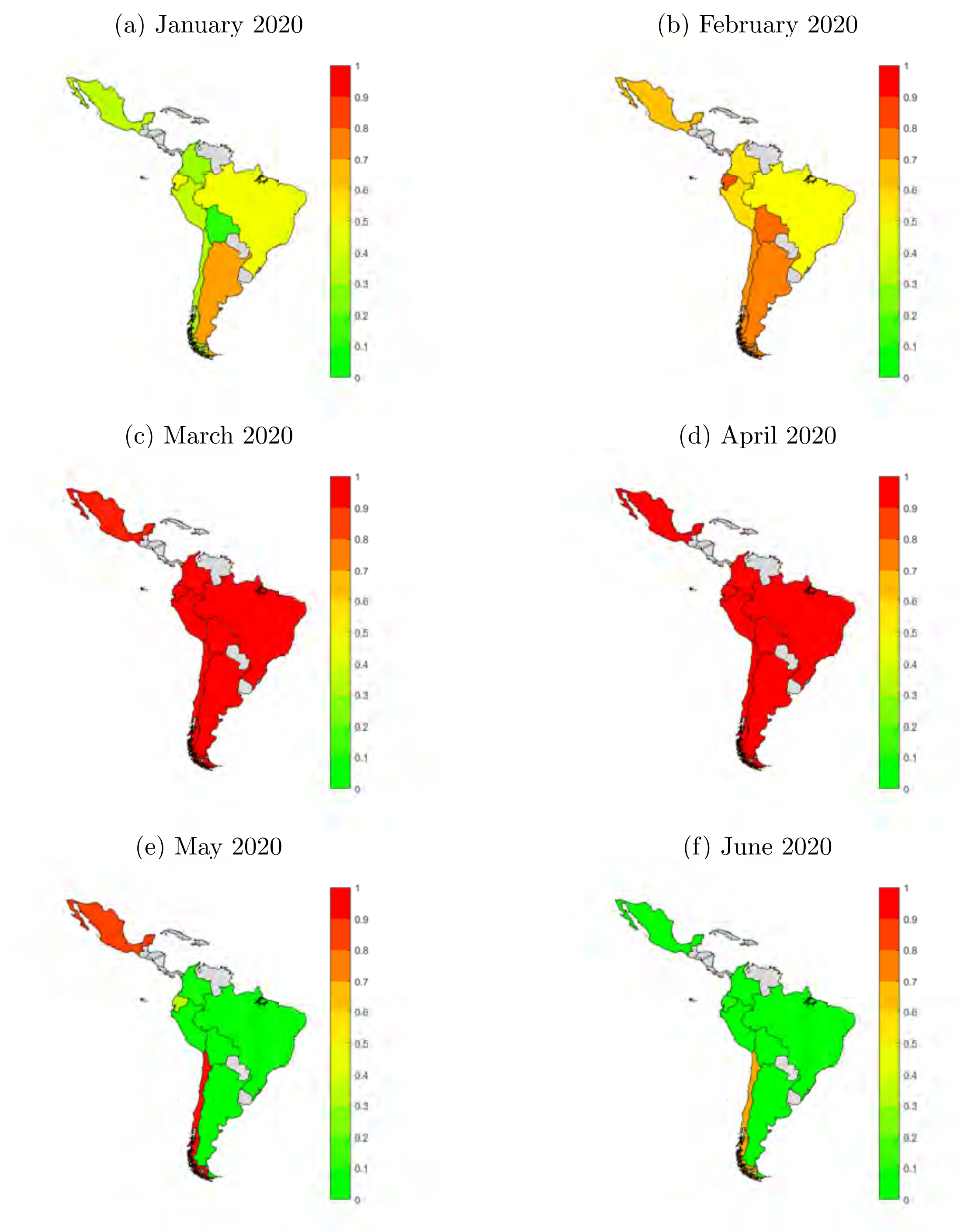
The nonlinear factor model (1)-(5) is independently fitted to eight of the largest Latin American economies; Argentina, Bolivia, Brazil, Chile, Colombia, Ecuador, Mexico and Peru. For each country, we not only collect information on real GDP, but also on additional indicators that are available at the 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 1, located in Online Appendix A. It is important to note that the employed data do not contain pandemics-related indicators, neither they are 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. To begin with, Figure 2 depicts maps of Latin America with the monthly evolution of the state probability during the first half of 2020, going from highly probable contraction in red to highly probable expansion in green.

The figure shows the rapid and synchronized switch to a recessionary phase exhibited by all countries of the region in March 2020, induced by the COVID-19 outbreak. This recessionary phase, despite of its intensity, which will be discussed later, lasted for only two months, that is, until April 2020.[4] Then, in May 2020, Argentina, Brazil, Colombia, Ecuador and Peru engaged in a recovery path, and in June 2020, Mexico also switched to an expansionary phase, while Chile remained in an uncertain state. The maps in Figure 2 illustrate the high importance of having at hand comprehensive statistics able to measure the state of the Latin America economies at the monthly frequency. Due to the fast-evolving economic environment, variables available at the quarterly frequency, or lower, would fail to capture these abrupt episodes in a timely fashion, as needed for policy makers.

[4]This is in line with the 2020:03−2020:04 recession in the U.S. economy, dated by the Business Cycle Dating Committee of the NBER.

Figure 2: Recession probabilities across countries during the COVID-19 outbreak



(a) January 2020

(b) February 2020

(c) March 2020

(d) April 2020

(e) May 2020

(f) June 2020

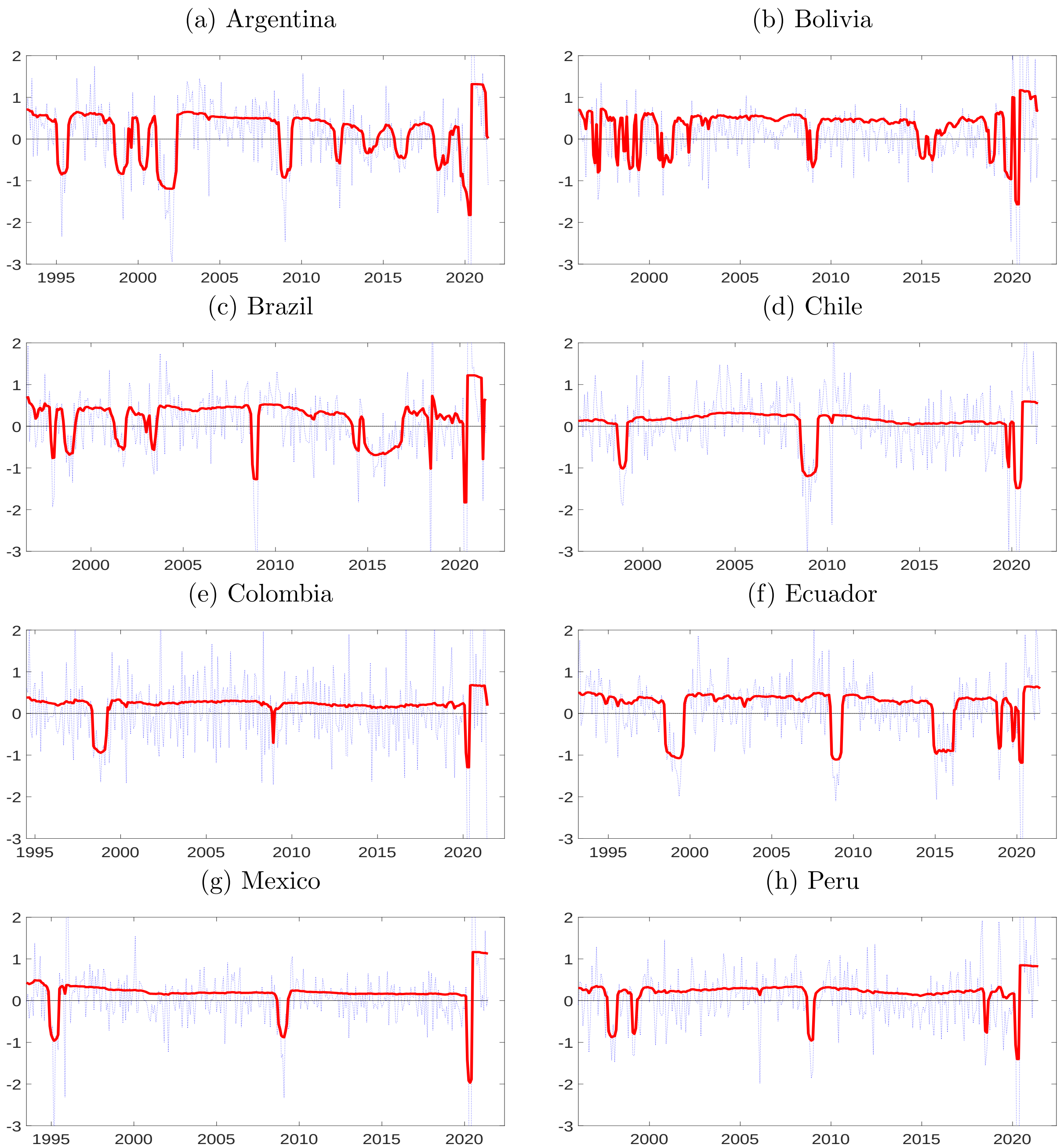
Note. The darker (lighter) the area associated with a country, the higher (lower) its probability of an economic recession. The animated sequence of heatmaps, from 1996:06 until 2021:05, can be found at: https://sites.google.com/site/daniloleivaleon/latam.

The entire history of the recession probabilities across countries are shown in charts C of figures 12 to 19, which are reported in Online Appendix C for the sake of space. By looking at these figures, it can be seen that the employed model successfully infers recessions and expansions of different magnitudes for all countries, thanks to its time-varying regime-dependent mean. In particular, it is shown that the so-called "Tequila crisis", originated in Mexico in 1994, extended to Argentina, Brazil and Peru. In addition, the effects that the Southeast Asia and Russian crises of 1997 had in LATAM can be identified, most notably in Argentina, Brazil, Chile, Ecuador and Peru. Regarding country-specific recessions, the model recognizes the Argentinean debt default of 2001, the Brazilian crisis following the political demonstrations of 2015, the Chilean crisis after the social outbreak of 2019, the Colombian banking crisis of 1999, the Ecuadorian recessions following the financial crisis of 1998-1999, the drop in oil prices in 2015 and the earthquake in 2016, the Peruvian crisis in 2003 caused by the Unions strikes originated in the Coca sector and the political crisis in Bolivia at the end of 2019.[5]

The second main object retrieved from the model is the common factor, or index of economic activity. The monthly indices corresponding to the eight countries are plotted in charts B of figures 12 to 19 in Online Appendix C, and present two distinct features. First, the unparalleled decline in activity during the COVID-19 pandemics experienced by all the countries, which was particularly larger in Argentina, Bolivia, Brazil and Mexico. Second, the noisiness of economic activity of these countries. This 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.

[5]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.

Figure 3: Real Momentum in Latin American Countries



Note: The solid red lines plot the real momentum, μ_t, for each country. The real momentum is defined as the intensity of growth that an economy exhibits during a given episode of expansion or recession. The dashed blue lines plot the index of economic activity, that is, the common factor f_t, for reference purposes. The vertical axis has been adjusted to provide a better visualization of real momentum, to see the original scale associated with the common factor, please, refer to the middle charts of figures 12-19 in Online Appendix C.

Figure (3) plot the real momentum of Latin American economies, also interpreted as the medium-term growth of real activity. The estimates show that the COVID-19 pandemics induced an atypical fall and rebound in the region, and also illustrate the heterogeneous intensity of recessions and booms both over time and across countries. In Argentina, three different contraction intensities can be identified. First, there are several crisis of medium intensity between 2010 and 2019. As explained by Campos (2020), Argentina experienced potential output stagnation and increasing output gap at the beginning of the 2010s, which ultimately led to high inflation, recurrent devaluations and periodic crisis. Second, there are two recessions of high intensity in the late 1990s and 2008, following the Asian and the 2008 subprime crisis, respectively. Third, there are extreme recessions, like the one at the early 2000s, after the sovereign debt default, and the COVID-19 crisis in 2020. For Brazil, Figure 3 shows recessions of two intensities. Most of the contractions, including the "Real" strong devaluation at the end 1990s and the political unrest in 2015, were moderate when compared with the subprime and the COVID-19 recessions.

The Bolivian case is similar to the Brazilian one, in the sense that recessions have two types of intensities as well. The fall of greater magnitude are associated with COVID-19, while those of lesser intensity correspond to the subprime crisis and the drop in commodity prices between 2015 and 2017. As for the rest of the countries, the real momentum displays fewer fluctuations. In Colombia, the subprime and the COVID-19 crisis were severe, but they were rather ephemeral when compared to the 1999 Banking crisis. On the other hand, those events had a much more persistent effect in Chile. As for Ecuador, three crises stand out which were milder but of a more permanent nature than the COVID-19 one. These are the financial crisis at the end of the 1990s, the subprime crisis in 2008 and the drop in commodity prices in 2015. For Mexico, the model identifies the "Tequila", Subprime and COVID-19 crises, being the latter about twice as deep as the previous ones. As for Peru, the real momentum describes few downturns (at the late 1990s and mid 2000s) which are much smaller than the COVID-19 recession.

Unlike recessions, the growth exhibited by Latin American economies during expansionary phases is relatively homogeneous over time. The only exception corresponds to the recovery from the COVID-19 crisis, in the second half of 2020. During this period, LATAM economies grew at unprecedented positive rates due to the reopening of activities and lifting of mobility restrictions.

To sum up, the features shown in Figure 3 point to an important asymmetry in the LATAM region, that is, recessions tend to be substantially heterogeneous in terms of magnitudes, while expansions are rather homogeneous. Overall, the information that the real momentum provides can help policy makers to optimally calibrate their monetary, fiscal or macroprudential measures according to the expected growth that the economy would exhibit during the ongoing business cycle phase.

4 New measures of the Latin American business cycle

A continuous monitoring of economic activity 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. As mentioned in the introduction of this manuscript, previous works on measuring short-term economic conditions in LATAM have mostly focused on the country-specific perspective. Instead, the high-frequency (monthly) measurement of the Latin American business cycle, as a single economic entity, has remained somewhat overlooked.

By employing the country-specific estimates presented in Section 3, we introduce here four 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, (ii) measurement of the momentum embedded in short-term fluctuations in activity, (iii) quantification of macroeconomic tail risks, and (iv) assessments on the overall economic activity.

4.1 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,

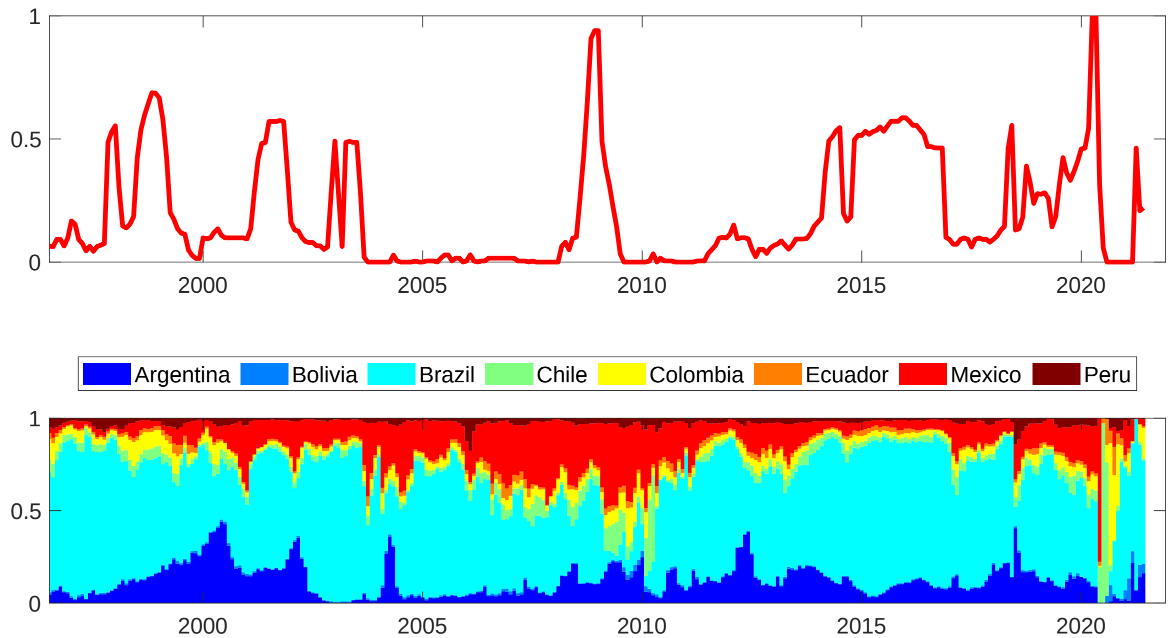
$$LAWI_t^{(l)} = \sum_{\kappa=1}^{K} \omega_{\kappa,t}(1 - s_{\kappa,t}^{(l)}), \tag{6}$$

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 4 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.

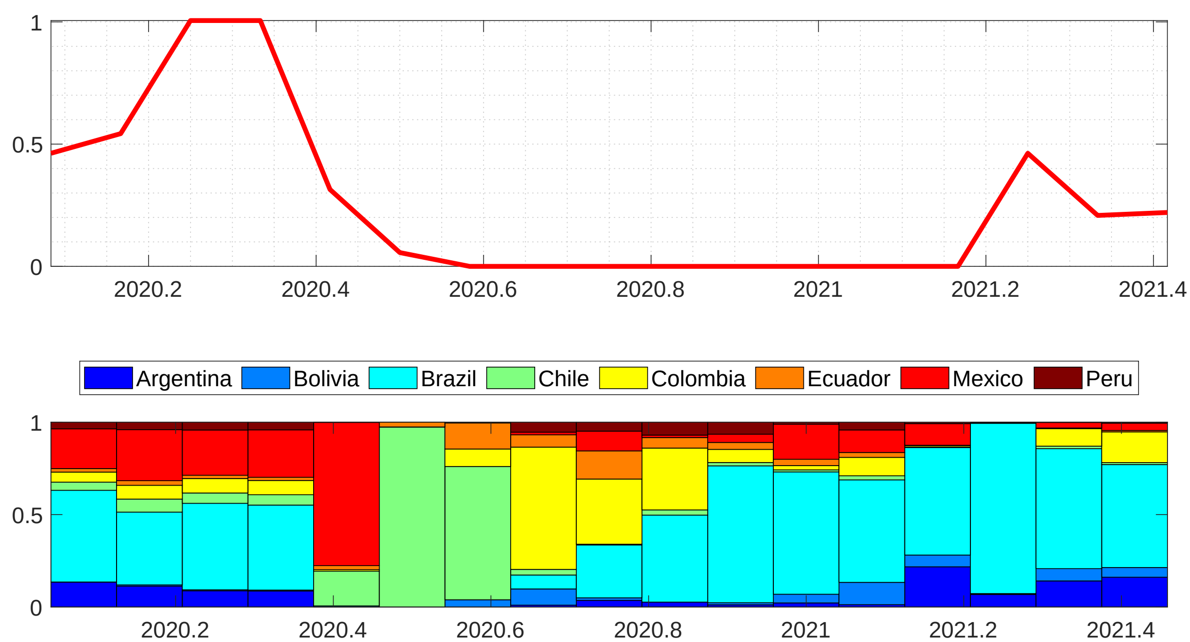
Chart A of Figure 4 shows LAWI's evolution between 1996 and 2021 along with the corresponding historical contribution of each country to such a weakness measures. The LAWI suggests that the region has gone through two clear episodes of recessions, which correspond to the "Great Recession" of 2008-2009 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.

Figure 4: Latin American Weakness Index (LAWI)

(a) Full sample: 1996:06−2021:05



(b) COVID-19 period: 2020:01−2021:05



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.

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, as shown in Figures 14 and 17, respectively, in Online Appendix C. 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 4 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 4 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, Chart A of Figure 20, located in Online Appendix C for the sake of space, shows the real-time LAWI, which is recursively estimated by adding one month of information at a time. The estimates suggest that the proposed index is able to provide robust and timely assessments on the degree of regional economic weakness, since it, first, resembles fairly well the full sample estimates reported in Figure 4, and second, acts as an early warning indicator of turning points when compared with real GDP annual growth reported by the World Bank.

4.2 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 defined 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,

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

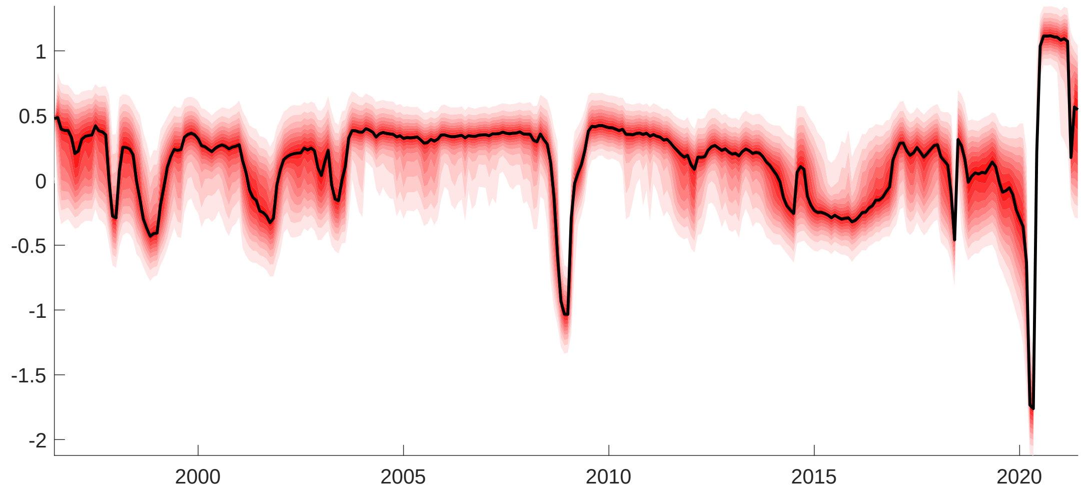
where K makes reference to the number of countries under consideration. The collection of all draws, $l = 1, ..., L$, constitutes the posterior density of the LAMI. Note that the momentum is a comprehensive measure that contains information on both the turning points assessment, through s_t, and on the size of fall and rebounds that the economy exhibits, through μ_{0,τ_0} and μ_{1,τ_1}. 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 will be studied in detail in the next section.

Chart A of Figure 5 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.

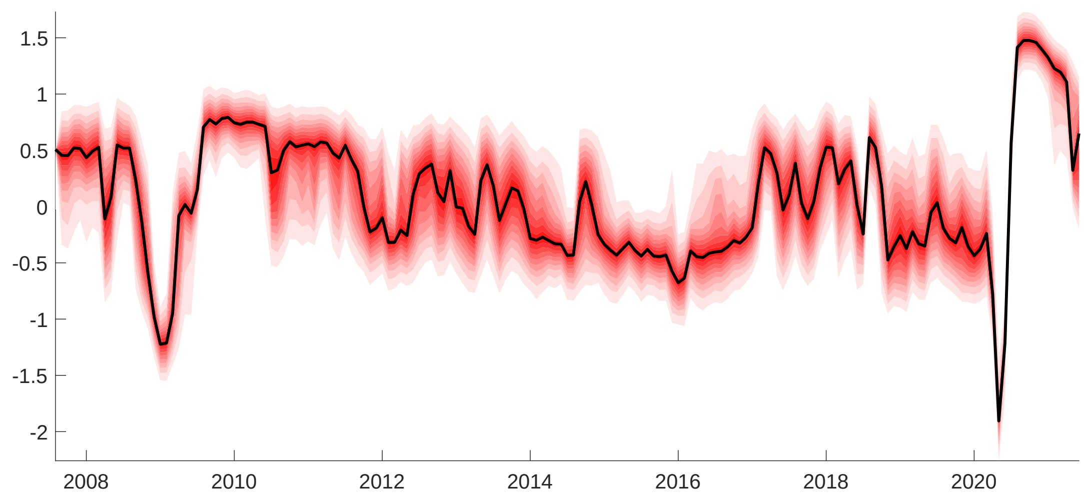
In terms of economic expansions, the LAMI identifies two types that can be labeled as “normal” and “abnormal” episodes of positive growth. The most common, or “normal”, expansionary phases are associated with LAMI values slightly below 0.5 standardized units. This is the average growth rate exhibited 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.

Figure 5: Latin American Momentum Index (LAMI)

(a) Full Sample Estimates



(b) Real-Time Estimates



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.

Overall, the LAMI helps to provide 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, recession 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 5, 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 could 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.

4.3 Tail Risks

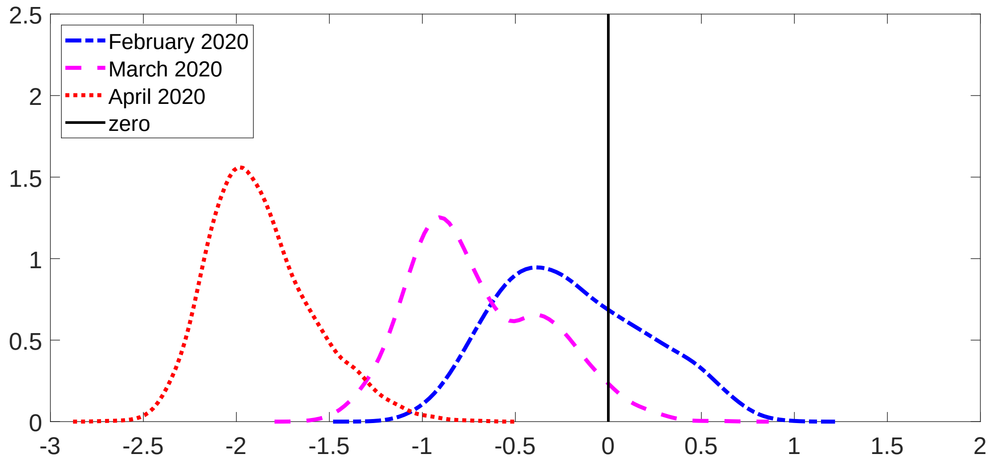
Due to the mounting risks induced by recent unprecedented global economic events, assessments on the distributional properties of macroeconomic activity can help policy makers to evaluate the likelihood of upcoming extreme scenarios in a context of high uncertainty, also known as tail risks. These properties are important to evaluate the resilience of the LATAM economy to contractionary shocks while the region faces a period of economic expansion. As well, distributional properties of real activity can provide information regarding upside or downside risks when the region is in the middle of a recession.

In this section, we propose two novel measures for measuring Latin American macroeconomic risks that provide a better understanding of the evolving levels of uncertainty embedded in LATAM's business cycle. In doing so, we dissect the posterior density of the LAMI in order to provide real-time assessments on (i) the size of macroeconomic tail risks in the region and (ii) how prone is LATAM's economic activity to exhibit extreme values.

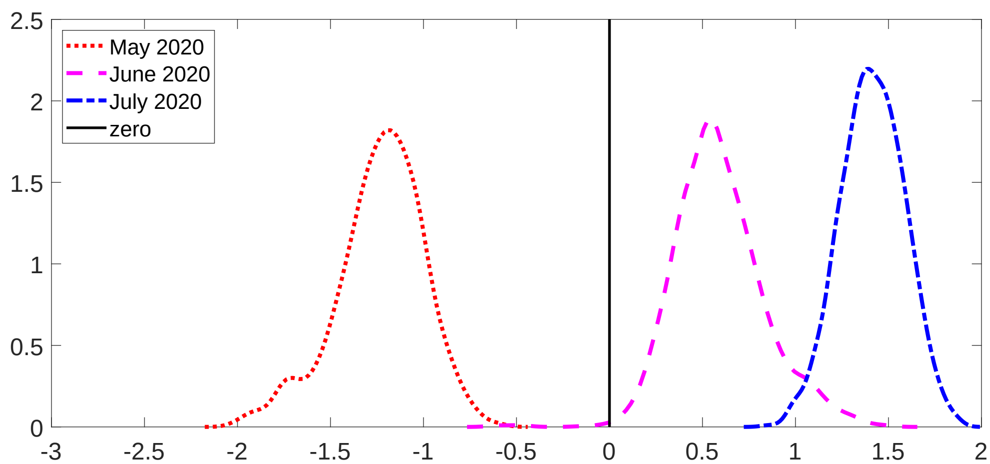
In order to illustrate how macroeconomic tail risks evolve over time, and particularly around turning points, we focus on the dynamics of LATAM's economy during the onset of the COVID-19 pandemics. Figure 6 shows the kernel posterior densities of the LAMI, estimated in real time, for selected months which correspond to the fall and rebound of economic activity induced by the pandemics.

Figure 6: Distribution of the Latin American Intensity Index for selected periods

(a) Fall



(b) Rebound



Note: Charts A and B plot the kernels of the LAMI posterior densities for months corresponding to the fall and rebound of economic activity in the region associated with the onset of the COVID-19 pandemics, respectively.

Chart A in Figure 6, focuses on the months corresponding to the beginning of the COVID-19 outbreak, that is, February, March and April of 2021. During these months the densities of the LAMI exhibited a rapid displacement towards the left, which was induced by the global economic collapse. Conversely, Chart B of Figure 6 plots the kernel densities of the LAMI corresponding to May, June and July 2020, associated to the subsequent recovery phase. Figure 21, placed in Online Appendix C for the sake of space, shows the entire sequence of the real-time LAMI's kernel densities for the entire sample period, illustrating the fast-evolving nature of macroeconomic risks in the Latin American economy.

Next, with the aim of providing a comprehensive assessment about the evolution of the tail risks embedded in LATAM's business cycle, we define two complementary measures referred to as Latin American Risk Assessment-Skewness (LARAS) and Latin American Risk Assessment-Kurtosis (LARAK), which make reference to the third and fourth moment of LATAM's business cycle time-varying distribution, respectively, measured by the posterior density of the LAMI. Let us start with the LARAS, which can be defined as,

$$LARAS_t = \mathbb{E}_{(l)} \left[\left(\frac{LAMI_t^{(l)} - mean(LAMI_t^{(l)})}{std(LAMI_t^{(l)})} \right)^3 \right]. \tag{8}$$

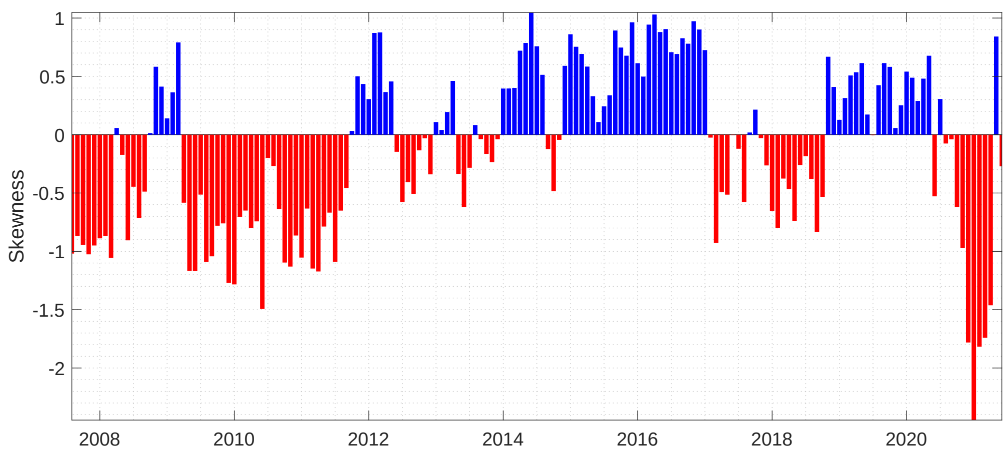
Chart A of Figure 7 reports the LARAS estimated in real time between July 2007 and May 2021. The estimates identify sustained periods of either upside or downside risks.

It is quite revealing to compare the kernel distributions in Chart A of Figure 6 with their corresponding skewness assessment in Chart A of Figure 7 during the COVID-19 fall at the beginning of 2020. And this is so because there are important differences regarding the degree of right-skewness in real activity distributions over those months. As the median of the distribution advanced through the negative territory, as shown in Chart A of Figure 6, the skewness of the LATAM business cycle, plotted in Chart A of Figure 7, increased from 0.29 in February to 0.48 in March, and then to 0.68 in April 2020. This implies that there were upside risks that signaled an increasing degree of optimism despite of the crisis, which is consistent with the sudden and abnormal nature of the "COVID-19 shock", not particularly driven by fundamentals.

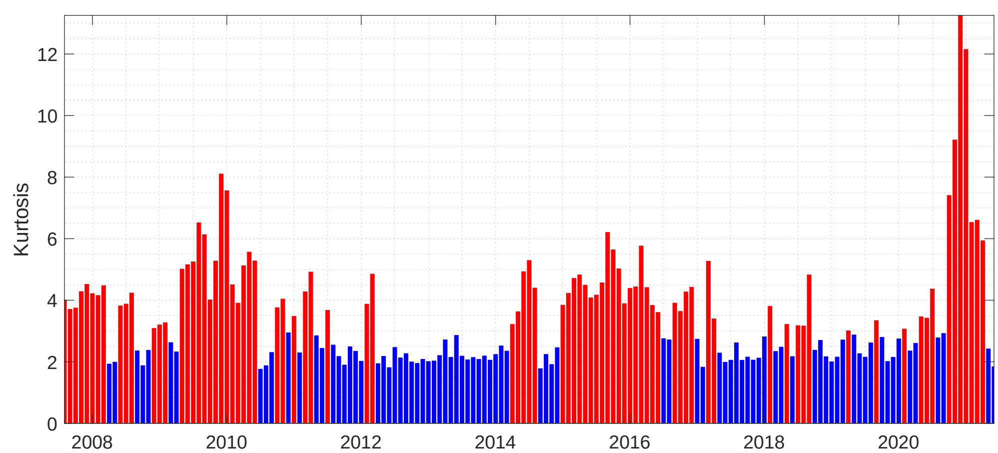
Rather, the kernel distributions of the LAMI associated to the subsequent recovery, shown in Chart B of Figure 6, exhibit a more heterogeneous degree of skewness. Actually, the corresponding skewness, plotted in Chart A of Figure 7 for May, June and July 2020, are -0.53, 0.30 and -0.07, respectively. These estimates illustrate the rapidly changing nature of tail risks when measuring macroeconomic conditions in LATAM, especially around turning points. Later on, the LARAS suggests that the amount of downside macroeconomic risks reached their maximum during the rebound after the COVID-19 crisis, with a skewness of -2.44 in December 2020, and started to recede since then.[6]

Figure 7: Latin American tail risk assessments through higher order moments

(a) Latin American Risk Assessment-Skewness (LARAS)



(b) Latin American Risk Assessment-Kurtosis (LARAK)



Note: Chart A plots the skewness of the time-varying posterior density of the LAMI, where blue (red) bars make reference to periods of macroeconomic upside (downside) risks, that is, with positive (negative) skewness. Chart B plots the kurtosis of the time-varying posterior density of the LAMI, where blue (red) bars indicate periods when activity is less (more) outlier-prone, that is, with values lower (higher) than 3. The sample covers the period 2007:07-2021:05.

[6]By relying on a nonparametric approach, Jensen et al. (2020) provide evidence of an increasing negative business cycle asymmetry over the last three decades for the U.S. economy and some G7 countries.

To complement the risk assessment of LATAM's business cycle performed thus far, the attention is next placed on the tails of its time-varying distribution, by measuring how outlier-prone it tends to be. In other words, we are interested in measuring the predisposition of LATAM economic activity to exhibit extreme values over the business cycle. By having in mind that distributions that are more outlier-prone than the normal distribution have kurtosis greater than 3, while distributions that are less outlier-prone have kurtosis less than 3, we rely on the LARAK to quantify such a predisposition. Accordingly, the LARAK can be defined as,

$$LARAK_t = \mathbb{E}_{(l)} \left[\left(\frac{LAMI_t^{(l)} - mean(LAMI_t^{(l)})}{std(LAMI_t^{(l)})} \right)^4 \right]. \tag{9}$$

Chart B of Figure 7 plots the real-time estimates of the LARAK, showing three periods where LATAM's activity has been more prone to exhibit extreme values. The first one corresponds to the recovery from the "Great Recession" in the second half of 2009 and early 2010. The second period corresponds to the decline in activity induced by the fall in commodity prices around the mid-2010s. The third period makes reference to the COVID-19 pandemics, when the LARAK exhibited the largest values in the sample under consideration.

It is important to note that the remarkable increase in the propensity of LATAM's activity to exhibit extreme values did not occurred during the COVID-19-induced economic fall, but during the subsequent rebound. The reasoning for this last result is as follows. Since the large fall in activity by the early 2020 was not based on fundamentals, there was no significant predisposition of LATAM's activity to behave in an abnormal or extreme manner. However, a few months after the pandemics hit, activity slowly restarted in the second half of 2020, and the amount of risks associated to experiencing a similar fall to the one just occurred substantially increased. The measurement of these type of risks can be useful for policy makers in the evaluation of different macroeconomic scenarios, which is precisely what the LARK is quantifying in real time.

The swings exhibited by both proposed risk measures, LARAS and LARAK, occasionally show countercyclical dynamics when compared with LATAM's GDP annual growth.

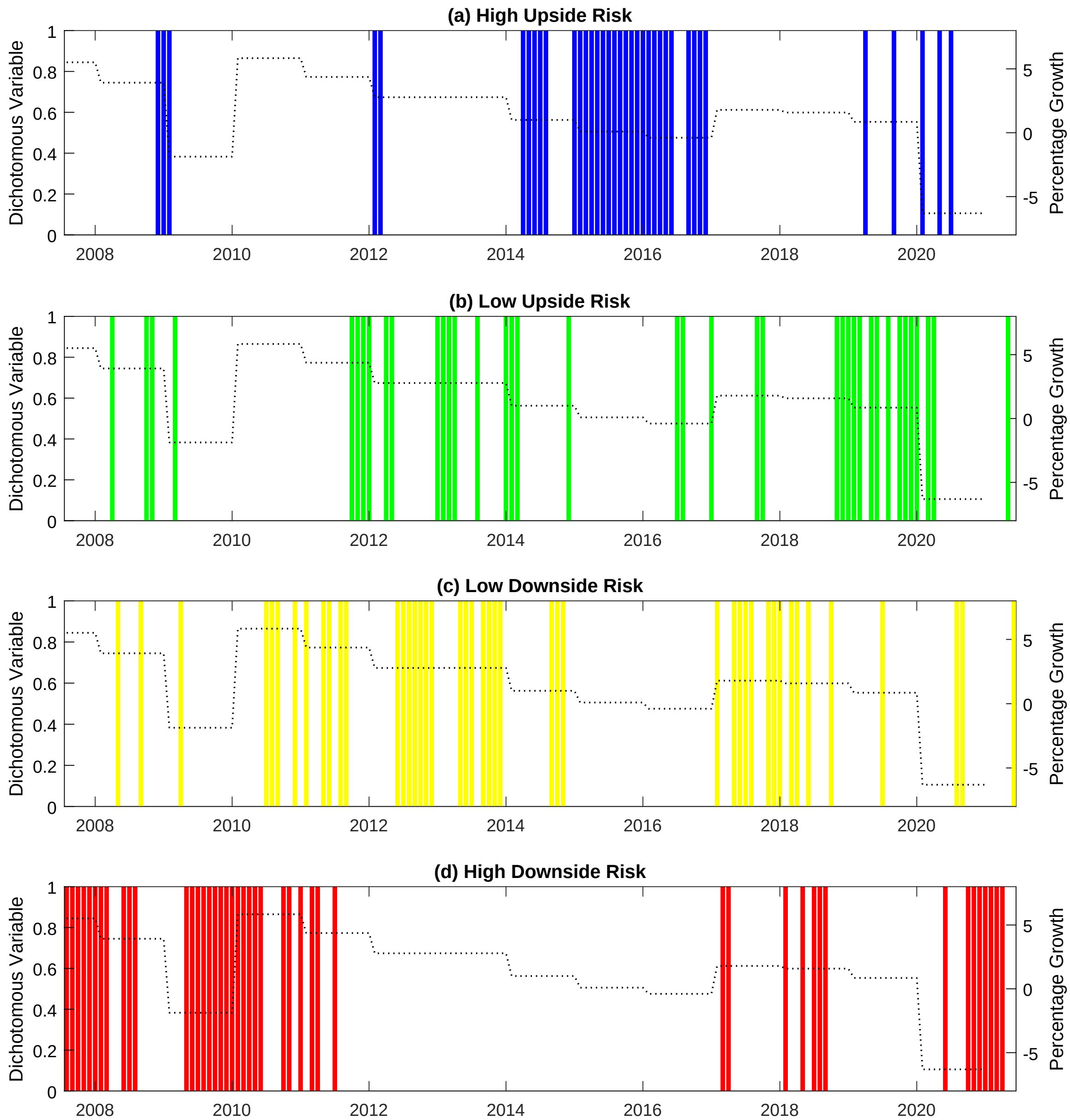
Charts B and C of Figure 20, in Online Appendix C, compare the LARAS and LARAK measures against the annual real GDP growth of Latin America and the Caribbean (reported by the World Bank), presenting a correlation of -0.19 and -0.39, respectively. In order to understand the underlying countercyclicality of the LARAS and LARAK, it is important to notice that these indices are constructed as weighted averages of country-specific estimates, where each rests on a two-state Markov-switching framework that provides a mixture of densities associated with the growth rate of the economy during expansion and recession. Figure 22, in Online Appendix C, presents an illustration on how a mixture of two densities evolves as the weights for each density, defined by the probability of recession, change over time. The figure shows that the size of downside (upside) risks during an expansion (recession) depends on both the inference on the state of the economy and the distribution of the expected growth rate during each phase of the business cycle, which in our framework also changes over time, allowing to provide a more detailed characterization of tails risks. Hence, the downside (upside) risks that could exhibit the LATAM economy during a period of expansion (recession) informs about the hypothetical scenario of a sudden regime change by characterizing it based on its likelihood and strength.

Next, based on information from the evolving skewness and kurtosis of LATAM's business cycle, we define four different types of tail risks that cover from the "best" to the "worst" scenario. The first type, also refereed to as "High Upside Risk", can be considered as the most favorable scenario since it is associated with upside macroeconomic risks and with high predisposition of real activity to exhibit extreme values. These events occur when the skewness is positive and the kurtosis is larger than 3 ($LARAS_t > 0$ and $LARAK_t > 3$). The blue bars in Figure 8 make reference to the months when these two conditions simultaneously apply, which tend to be concentrated between 2014 and 2017. This was precisely when the commodity supercycle was over and the region was experiencing low growth.

The second type is referred to as "Low Upside Risk" and is also consistent with upside tail risks, but in this case, the predisposition to outliers in the distribution is smaller, i.e. with a kurtosis lower than 3 ($LARAS_t > 0$ and $LARAK_t < 3$). Green bars in Figure 8 identify the months when these events take place, which are more spread over the sample. Nevertheless, the years 2019 and early 2020 can be identified with "Low Upside Risk".

Even before the pandemic, the region was already showing languid growth and there was a moderate upside risk.

Figure 8: Types of Latin American Macroeconomic Tails Risks



Note. The figure provides a real-time identification of the months associated with each of the four different types of macroeconomic tail risk, defined as, High Upside, Low Upside, Low Downside and High Downside. The dotted black line makes reference to the annual GDP growth of Latin America and the Caribbean, as published by the World Bank, which is aligned with the right axis. The sample covers the period 2007:07-2021:05.

The third type corresponds to a soft adverse scenario, also referred to as "Low Downside Risk", which is consistent with a negatively skewed distribution that is relatively low outlier-prone, i.e. with a kurtosis lower than 3 ($LARAS_t < 0$ and $LARAK_t < 3$). Yellow bars in Figure 8 make reference to the months where this type of risk is present. Similarly to the previous case, low downside risks do not tend to be clustered over time. If anything, there seems to be some concentration of moderate downside risks between 2012 and 2014, when the region was still benefiting from high commodity prices.

The last type corresponds to the most adverse risk, where negative downside pressures are present, and in addition, there is a high predisposition of real activity to exhibit extreme values ($LARAS_t < 0$ and $LARAK_t > 3$). Accordingly, this type is referred to as "High Downside Risk" and is represented by read bars in Figure 8. The periods when this type of risk is more present correspond to the onset and aftermath of the "Great Recession" and to the recovery from the COVID-19 pandemics.

4.4 Overall Activity

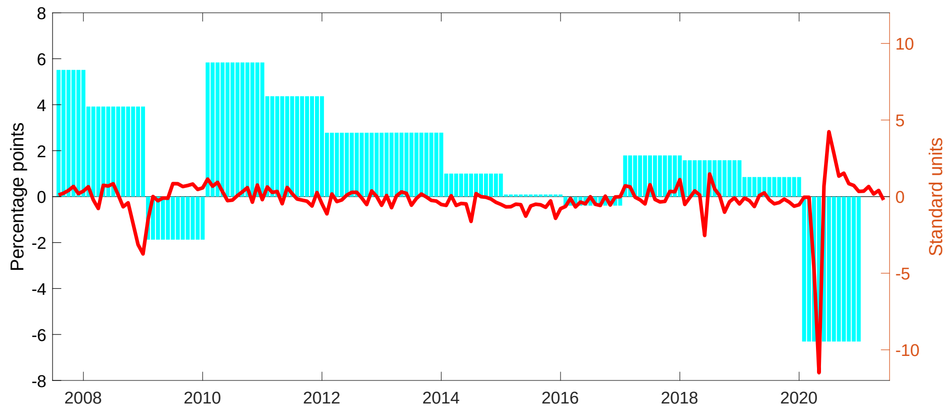
The last measure of Latin American business cycle that we propose in this paper is associated with more standard metrics that are usually employed to monitor short-term economic developments in real time. By averaging the country-specific indices of economic activity, f_t, extracted from the nonlinear factor model described in Section 2, we construct the Latin American Activity Index (LACI). For each time period, the LACI is calculated only with the information available at the time of the estimation. Hence, the index provides real-time assessments on real activity growth for a given month. Due to the Bayesian estimation environment, the LACI can be defined as,

$$LACI_t = \frac{1}{L} \sum_{l=1}^{L} \left[\sum_{\kappa=1}^{K} \omega_{\kappa,t} f_{\kappa,t}^{(l)} \right], \tag{10}$$

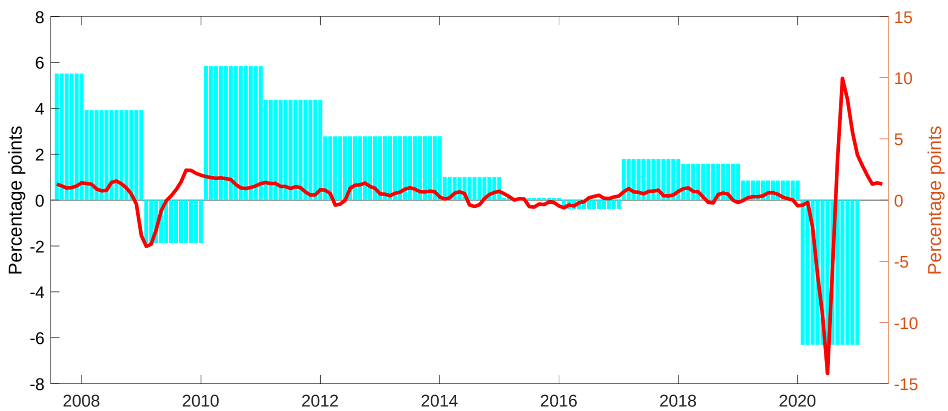
where K and L make reference to the number of countries and number of Bayesian iterations. Chart A of Figure 9 plots the LACI against the annual GDP growth of Latin American and the Caribbean, showing that the index is able to anticipate falls in LATAM's GDP with a substantial lead. In particular, it provided timely information on the unprecedented fluctuations induced by the COVID-19 pandemics by reporting a value of -4.8% in March 2020, and reaching its historical low of -11.5% in April 2020. Also, the LACI promptly signaled the sizeable recovery by reaching its historical maximum of 4.2% in June 2020.

Figure 9: Latin American Activity Index (LACI)

(a) Monthly Inferences on Monthly Growth of Activity



(b) Monthly Inferences on Quarterly Growth of Activity



Note. The red line in Chart A makes reference to the monthly growth activity index computed as the weighted average among the country-specific indices of economic activity, f_t. The red line in Chart B makes reference to the quarterly growth activity index computed as the weighted average among the country-specific "counterfactual" measure of monthly real GDP growth. Both measures are computed in real-time. Cyan bars indicate annual real GDP growth of Latin America and the Caribbean, as reported by the World Bank. The sample covers the period 2007:07-2021:05.

Since the LACI is expressed in standardized units, we transform the index into a measure that is expressed in terms of quarterly GDP growth rates for ease of interpretation and comparability. In doing so, we focus on the projected GDP that is produced through Equation (1), denoted as $\widetilde{GDP}_t$. It is important to note that $\widetilde{GDP}_t$ provides inferences on quarterly GDP growth associated with month t, therefore, it can be interpreted as a proxy for a counterfactual monthly GDP. This transformation of the index is defined as,

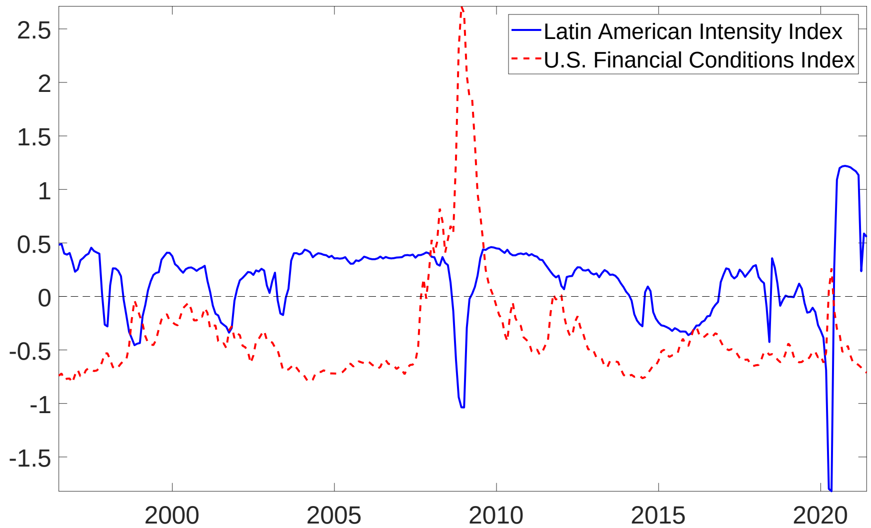
$$LACI_t^* = \frac{1}{L}\sum_{l=1}^{L}\left[\sum_{\kappa=1}^{K}\omega_{\kappa,t}\widetilde{GDP}_{\kappa,t}^{(l)}\right]. \tag{11}$$

Chart B of Figure 9 plots the LACI* showing its ability to provide a timely real-time tracking of periods when LATAM's GDP falls into negative or positive territory. In particular, the LACI* exhibits its lowest value in May 2020, with -14%, and its maximum in September 2020, with 10%. These figures represent the bottom and top of the LATAM economy during the COVID-19 crisis, respectively. In sum, this index provides valuable information considering the substantial delay that the release of GDP official statistics takes in Latin American and the Caribbean.

5 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 10 plots the LAMI, described in Section 4.2, 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 10: 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 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,

$$LAMI_t^{(l)} = \alpha_t^{(l)} + \beta_t^{(l)} FCI_t + \gamma_t^{(l)} C19_t + e_t^{(l)}, \tag{12}$$

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.[7] Particularly, we define the following control variable,

$$C19_t = \begin{cases} 0 & \text{If } \; t \leq \tau \\ mobility_t & \text{If } \; t > \tau \end{cases} \tag{13}$$

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 (12), we allow the intercept and all slope parameters to evolve according to random walk dynamics,

$$\alpha_t^{(l)} = \alpha_{t-1}^{(l)} + v_t^{(l)} \tag{14}$$

$$\beta_t^{(l)} = \beta_{t-1}^{(l)} + \nu_t^{(l)} \tag{15}$$

$$\gamma_t^{(l)} = \gamma_{t-1}^{(l)} + u_t^{(l)} \tag{16}$$

where $v_t^{(l)} \sim N(0, \sigma_v^{(l)})$, $\nu_t^{(l)} \sim N(0, \sigma_\nu^{(l)})$ and $u_t^{(l)} \sim N(0, \sigma_u^{(l)})$.[8]

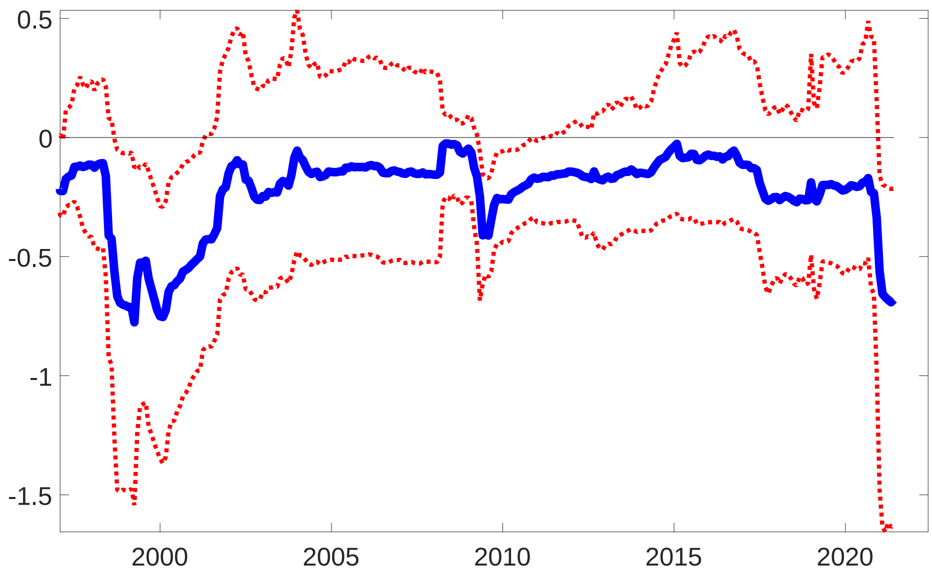
Figure 11 plots the estimated slope coefficient, β_t, showing a significantly negative impact during three specific periods when tighter U.S. financial conditions were associated with smaller medium-term growth of Latin American economic activity. The first one corresponds to the late 1990s and early 2000s, which coincides with a tightening in U.S. monetary policy, also reflected in a prolonged period of tighter 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

[7] 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.

[8] 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 (12), as measurement, and equations (14)-(16), as transition. The parameters are estimated by maximum likelihood.

to the second half of 2020. During this period, U.S. financial conditions became temporarily tighter, however, 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.

Figure 11: 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 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.[9]

[9]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.

6 Conclusions

In this paper, we provide a new set of 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. Moreover, 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".

Next, with the aim of providing a better understanding of the evolving levels of uncertainty embedded in LATAM's business cycle, the distributional properties of the LAMI are exploited. In doing so, we propose two measures referred to as Latin American Risk Assessment-Skewness (LARAS) and Latin American Risk Assessment-Kurtosis (LARAK). These measures provide real-time assessments on (i) the size of macroeconomic tail risks in the region and (ii) how prone is LATAM's economic activity to exhibit extreme values, respectively. Additionally, we provide a Latin American Activity Index (LACI) that proves to follow closely overall regional activity and, as such, can be used to obtain timely nowcasts of LATAM's GDP growth.

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.

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A Data

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 used for each country

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

* 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:

$$\mu_{0,t} = (1 - d_{0,t})\mu_{0,t-1} + d_{0,t}\mu_{0,\tau_0}, \tag{17}$$

$$\mu_{1,t} = (1 - d_{1,t})\mu_{1,t-1} + d_{1,t}\mu_{1,\tau_1}, \tag{18}$$

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:

$$\mu_{0,\tau_0} \sim \mathcal{N}(\bar{\mu}_{0,\tau_0}, \sigma^2_{\mu_{0,\tau_0}}) \text{ i.i.d.}, \tag{19}$$

$$\mu_{1,\tau_1} \sim \mathcal{N}(\bar{\mu}_{1,\tau_1}, \sigma^2_{\mu_{1,\tau_1}}) \text{ i.i.d.} \tag{20}$$

That is, each recessionary and expansionary episode has its own unique mean of the common factor, which is independent of other episodes.[10] 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.

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

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:

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

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).[11]

In order to extract the common factor, the non-linear dynamic factor model is cast in a state-space form. Let vector $y_t = [y_t^q, y_{1,t}^m, ..., y_{M,t}^m]'$ 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 in period t, they can be related to their unobserved idiosyncratic components and the common factor as follows:

$$y_t = \mathbf{H} z_t + \eta_t, \quad \eta_t \sim \mathcal{N}(0, \mathbf{R}). \tag{21}$$

[11]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 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:

$$y_t^* = \mathbf{H}_t z_t + \eta_t^*, \quad \eta_t^* \sim \mathcal{N}(0, \mathbf{R}_t), \tag{22}$$

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:

$$z_t = \boldsymbol{\mu}_t + \mathbf{F} z_{t-1} + \varepsilon_t, \quad \varepsilon_t \sim \mathcal{N}(0, \mathbf{Q}), \tag{23}$$

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 (17) and (18), 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 (22)-(23).

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).

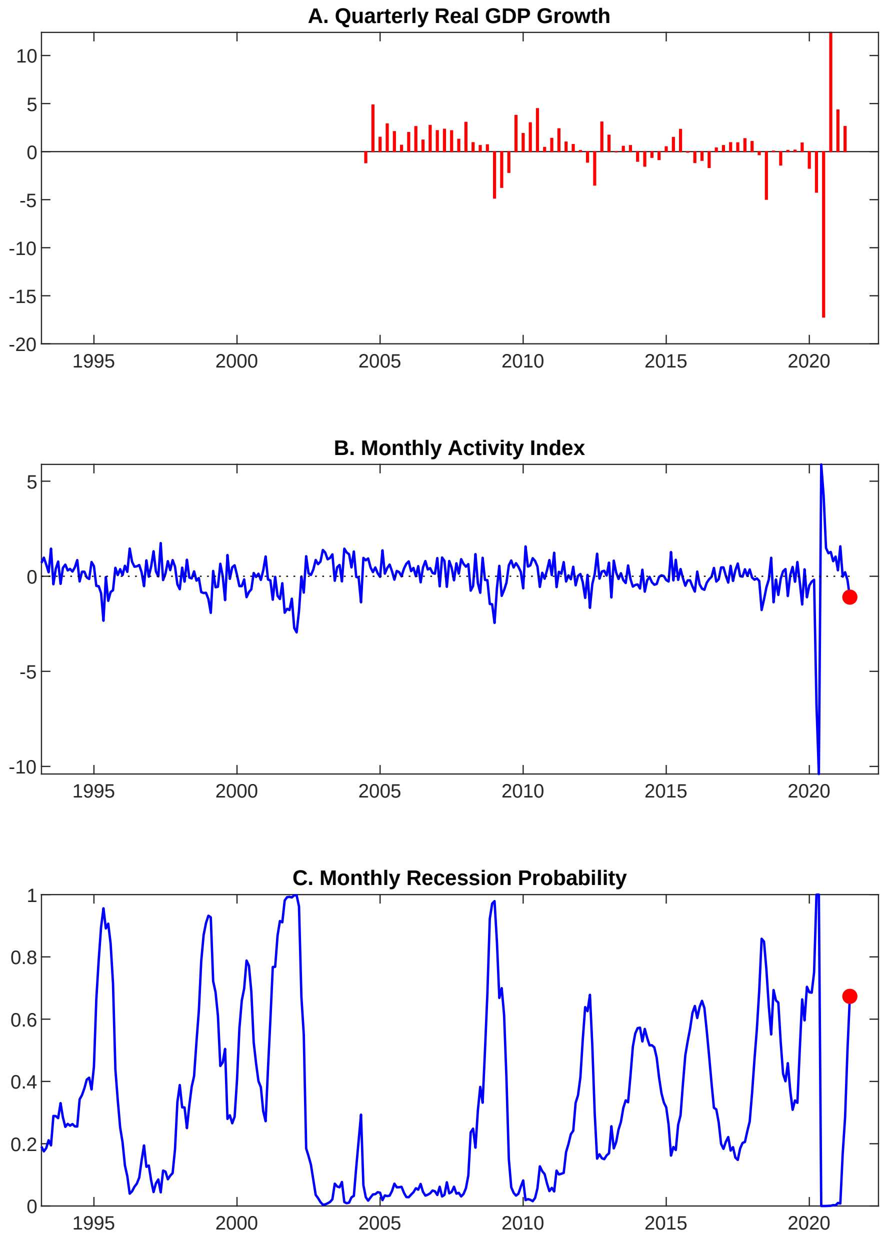
3. Given Y, Z^l, S^l, and μ^l, simulate θ^l using the Gibbs sampler and the standard conjugate prior distributions.

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 (17) and (18). 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.

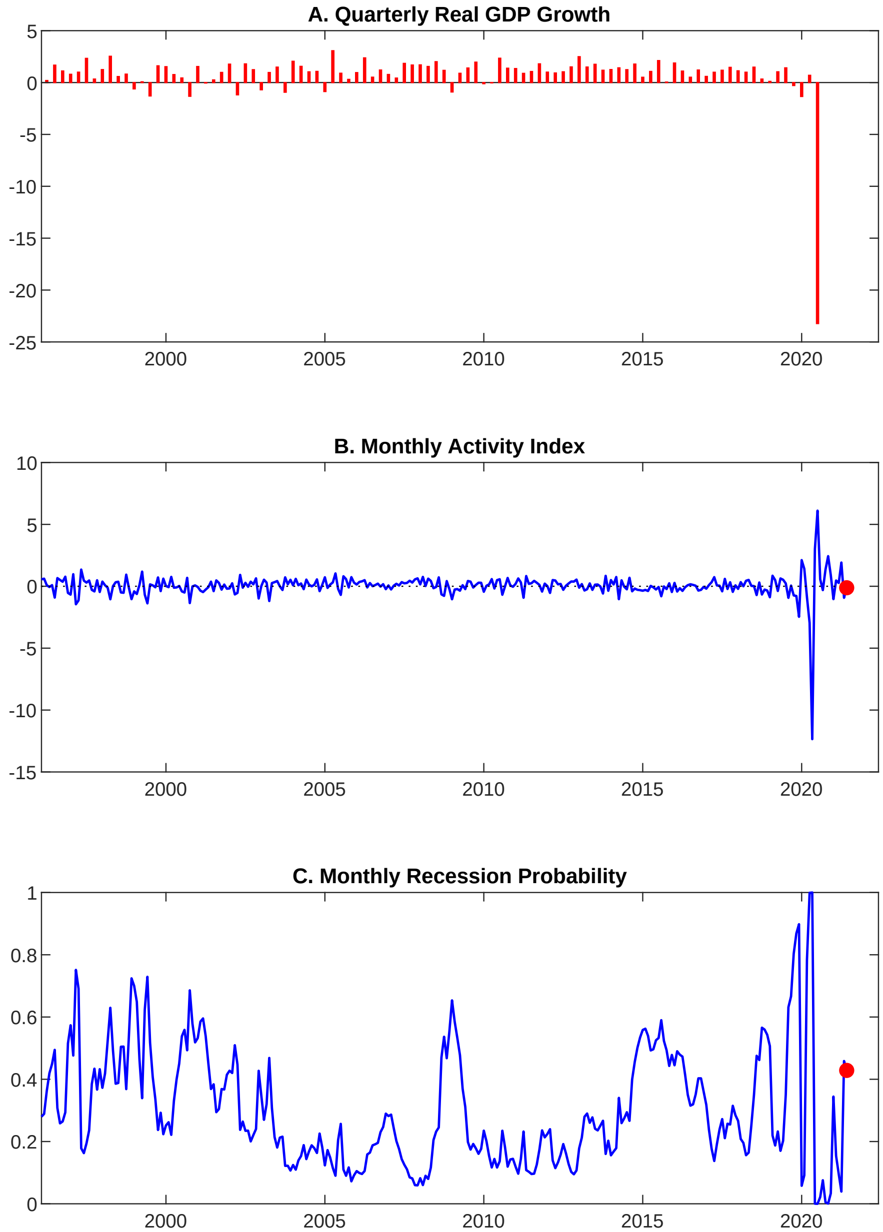
C Additional Figures

Figure 12: State of the Economy of Argentina



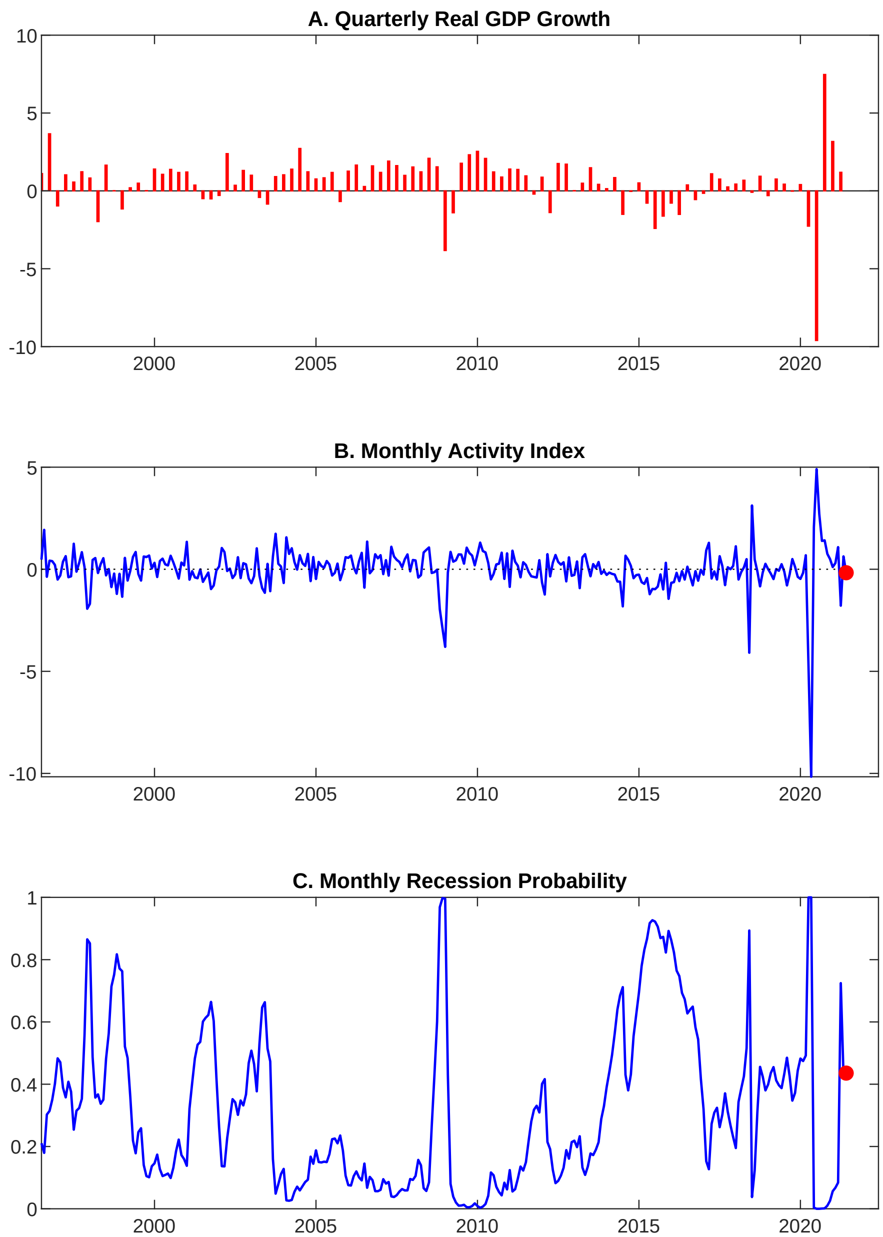
Note: The figure plots the estimated monthly activity index (Chart B) and time-varying recession probability (Chart C) obtained with a regime switching dynamic factor model with and heterogeneous means. Quarterly real GDP growth is also reported in Chart A for comparison purposes.

Figure 13: State of the Economy of Bolivia



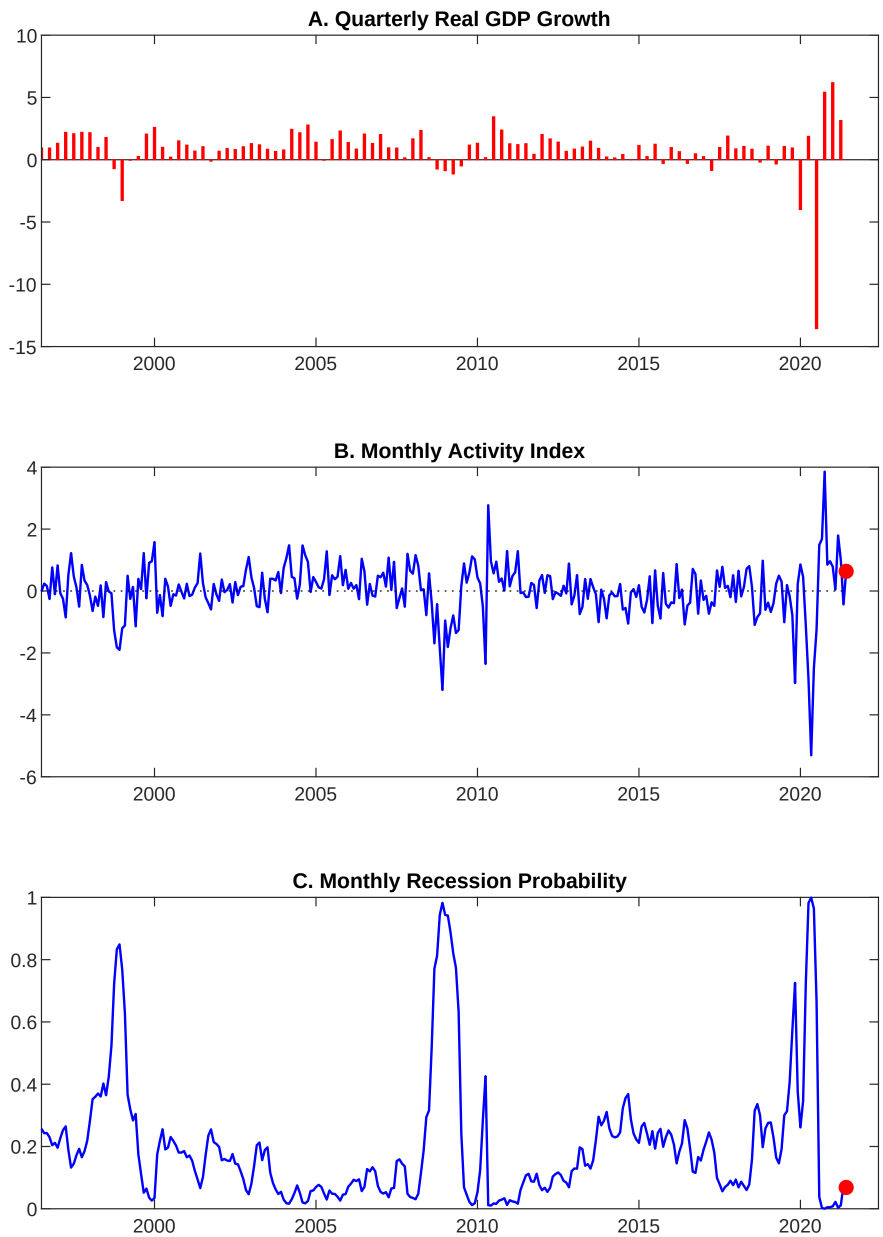
Note: The figure plots the estimated monthly activity index (Chart B) and time-varying recession probability (Chart C) obtained with a regime switching dynamic factor model with and heterogeneous means. Quarterly real GDP growth is also reported in Chart A for comparison purposes.

Figure 14: State of the Economy of Brazil



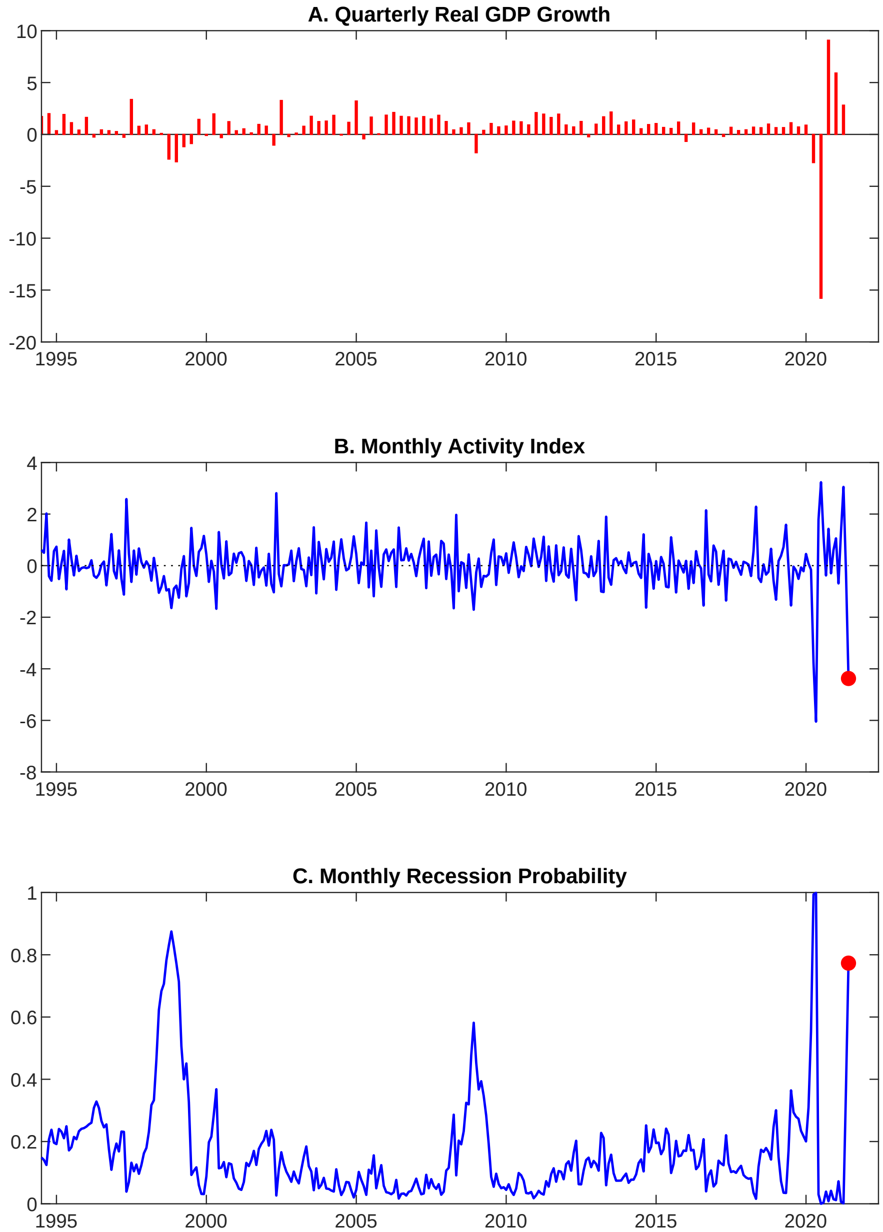
Note: The figure plots the estimated monthly activity index (Chart B) and time-varying recession probability (Chart C) obtained with a regime switching dynamic factor model with and heterogeneous means. Quarterly real GDP growth is also reported in Chart A for comparison purposes.

Figure 15: State of the Economy of Chile



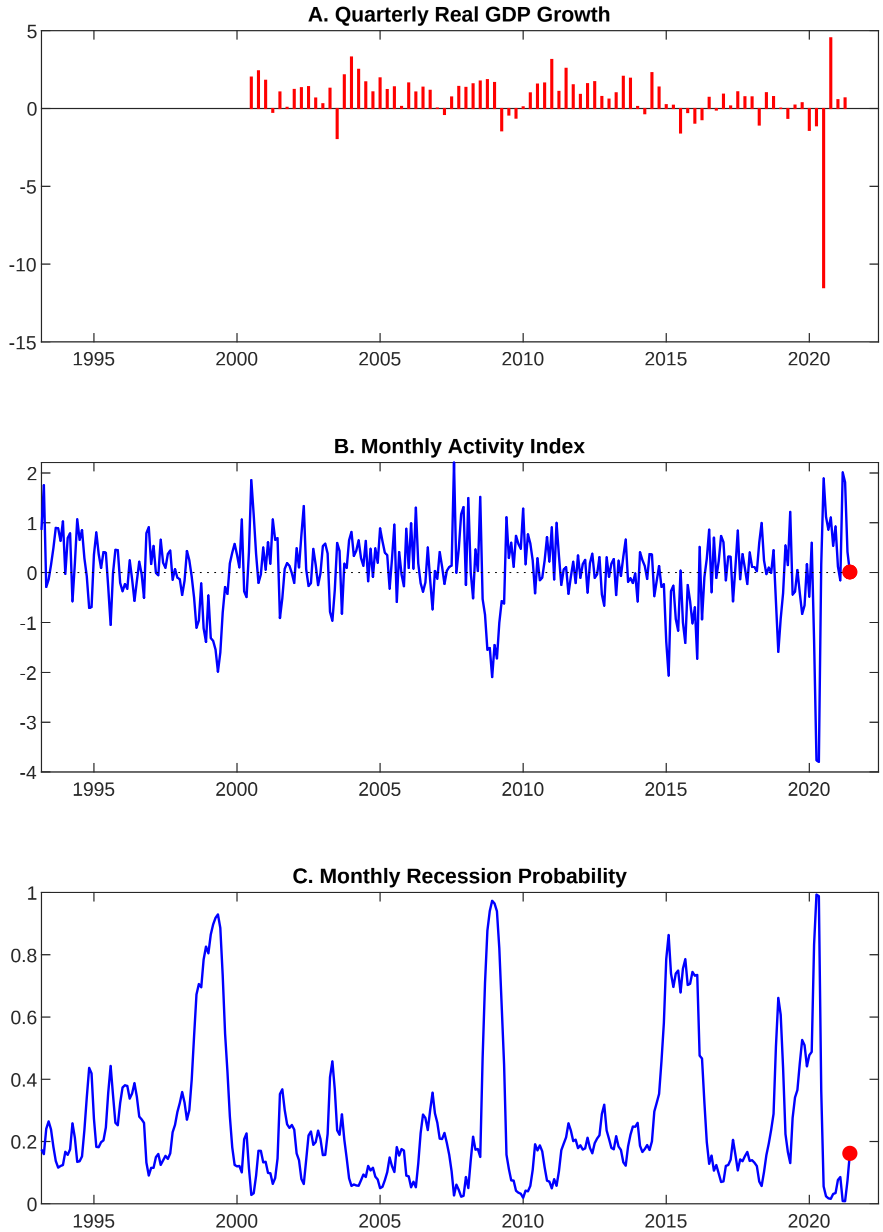
Note: The figure plots the estimated monthly activity index (Chart B) and time-varying recession probability (Chart C) obtained with a regime switching dynamic factor model with and heterogeneous means. Quarterly real GDP growth is also reported in Chart A for comparison purposes.

Figure 16: State of the Economy of Colombia



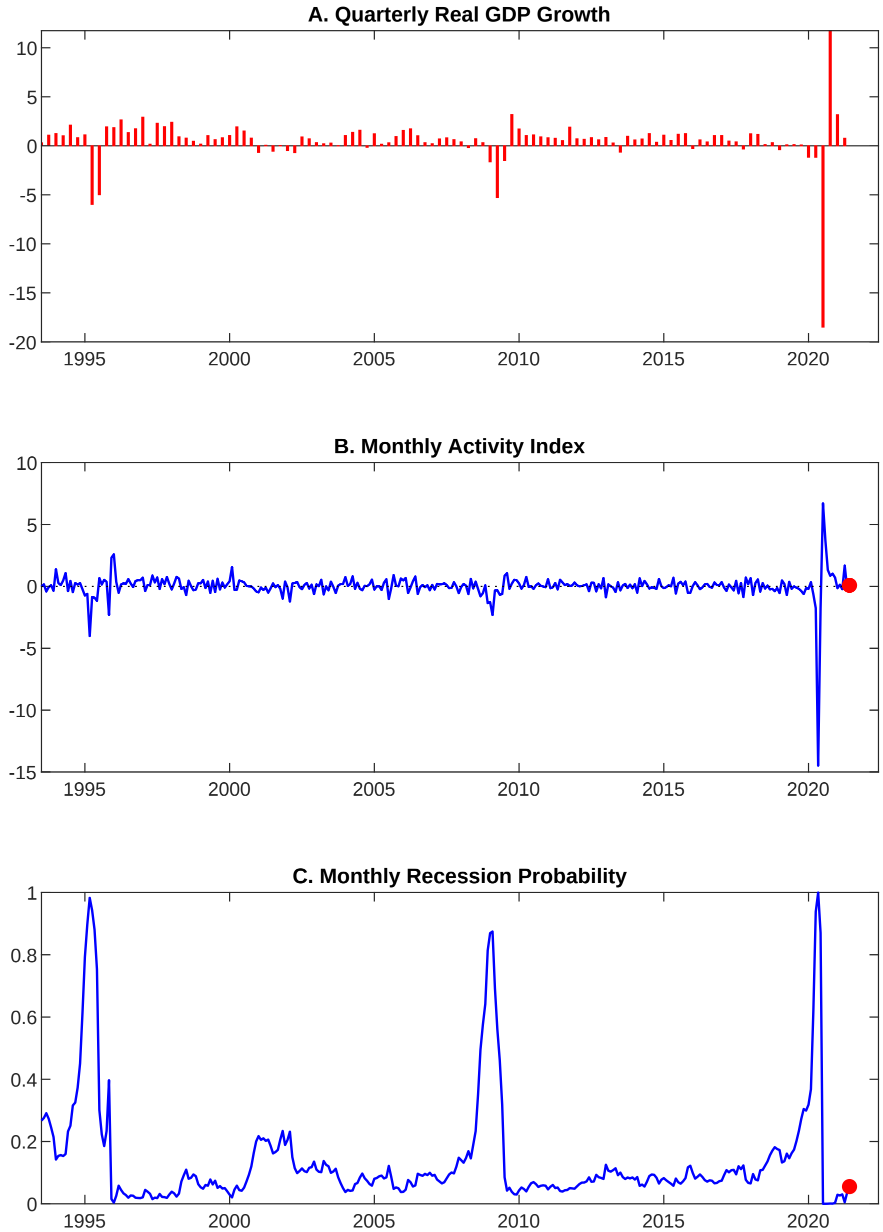
Note: The figure plots the estimated monthly activity index (Chart B) and time-varying recession probability (Chart C) obtained with a regime switching dynamic factor model with and heterogeneous means. Quarterly real GDP growth is also reported in Chart A for comparison purposes.

Figure 17: State of the Economy of Ecuador



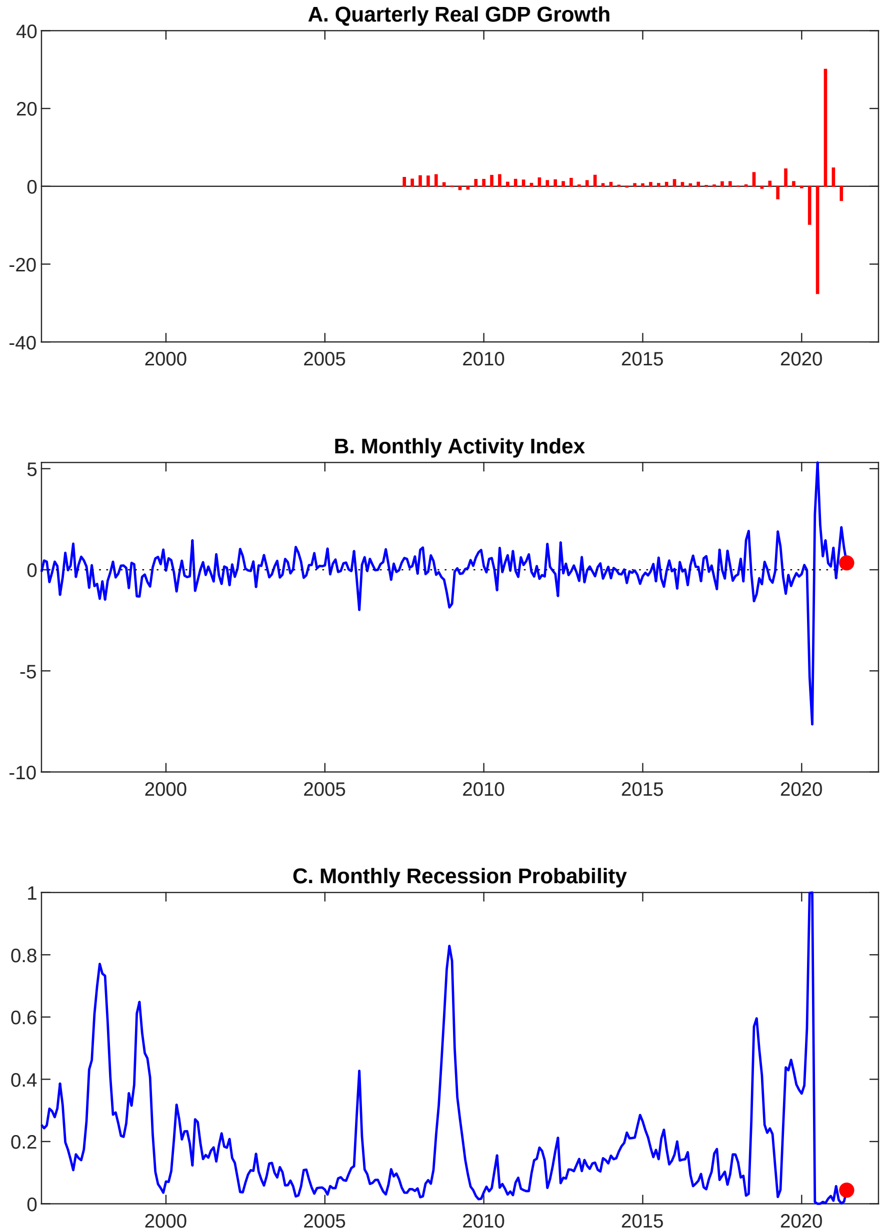
Note: The figure plots the estimated monthly activity index (Chart B) and time-varying recession probability (Chart C) obtained with a regime switching dynamic factor model with and heterogeneous means. Quarterly real GDP growth is also reported in Chart A for comparison purposes.

Figure 18: State of the Economy of Mexico



Note: The figure plots the estimated monthly activity index (Chart B) and time-varying recession probability (Chart C) obtained with a regime switching dynamic factor model with and heterogeneous means. Quarterly real GDP growth is also reported in Chart A for comparison purposes.

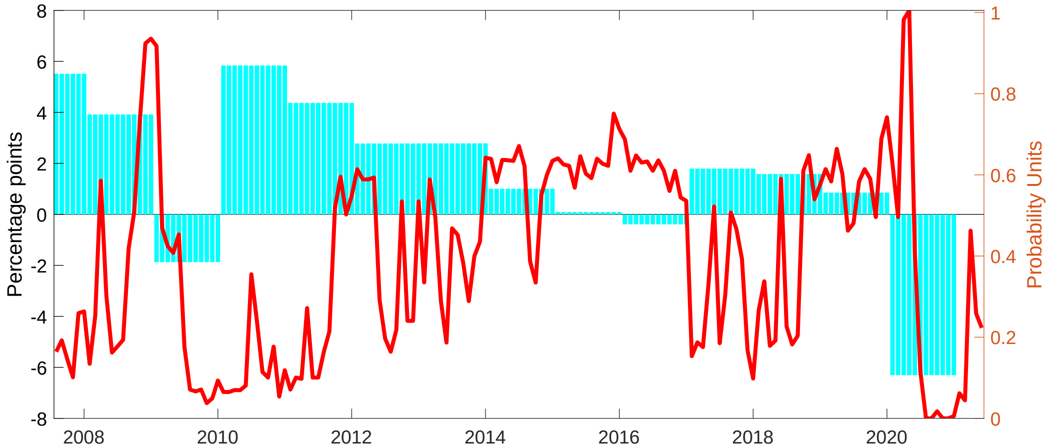
Figure 19: State of the Economy of Peru



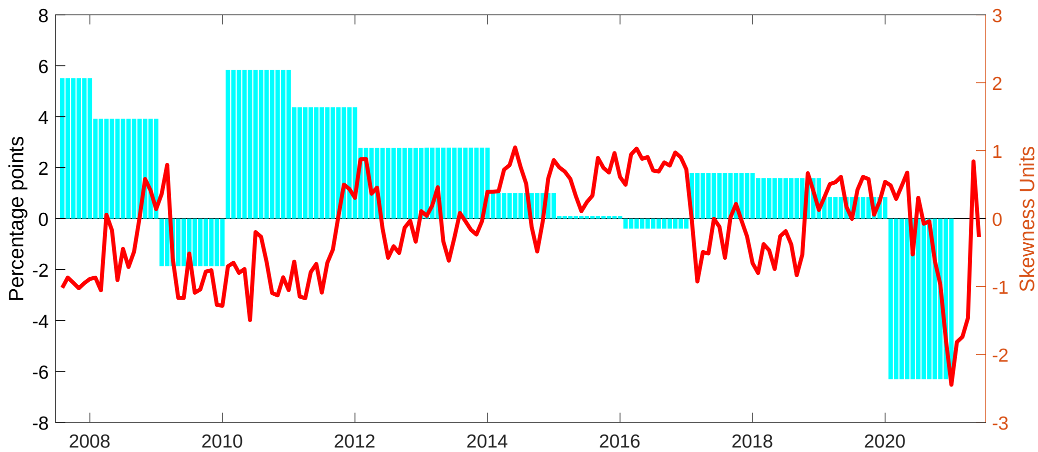
Note: The figure plots the estimated monthly activity index (Chart B) and time-varying recession probability (Chart C) obtained with a regime switching dynamic factor model with and heterogeneous means. Quarterly real GDP growth is also reported in Chart A for comparison purposes.

Figure 20: Comparison between the new measure of LATAM business cycle and real GDP

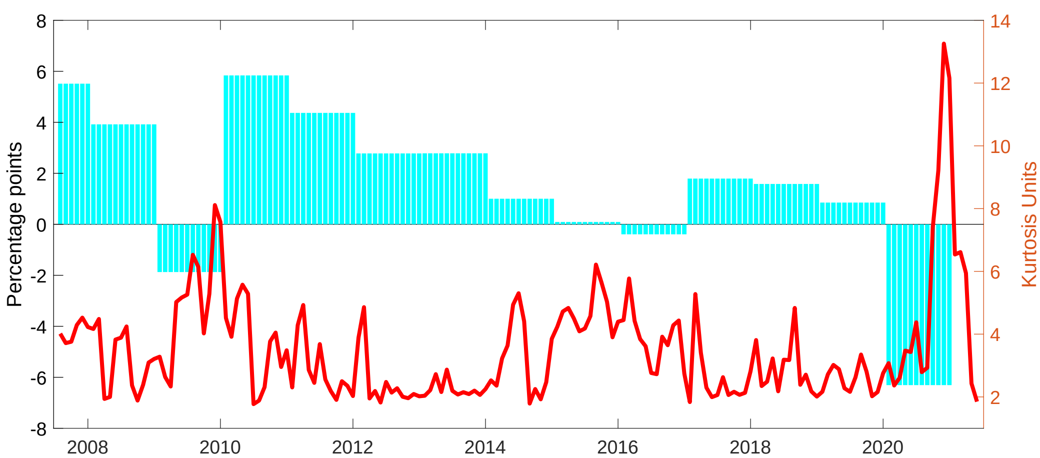
(a) Real-Time Latin American Weakness Index (LAWI)



(b) Real-Time Latin American Risk Assessment-Skewness (LARAS)

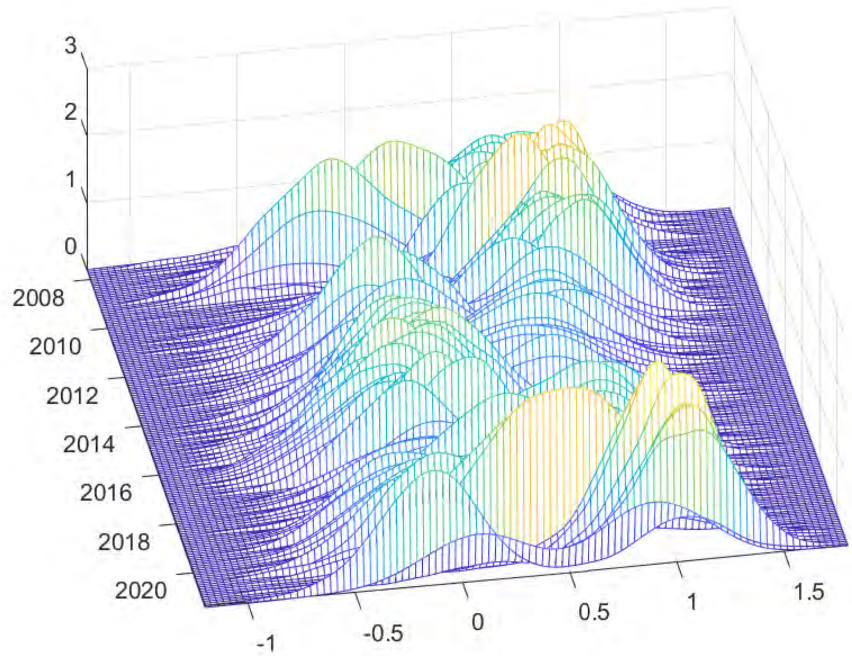


(c) Real-Time Latin American Risk Assessment-Kurtosis (LARAK)



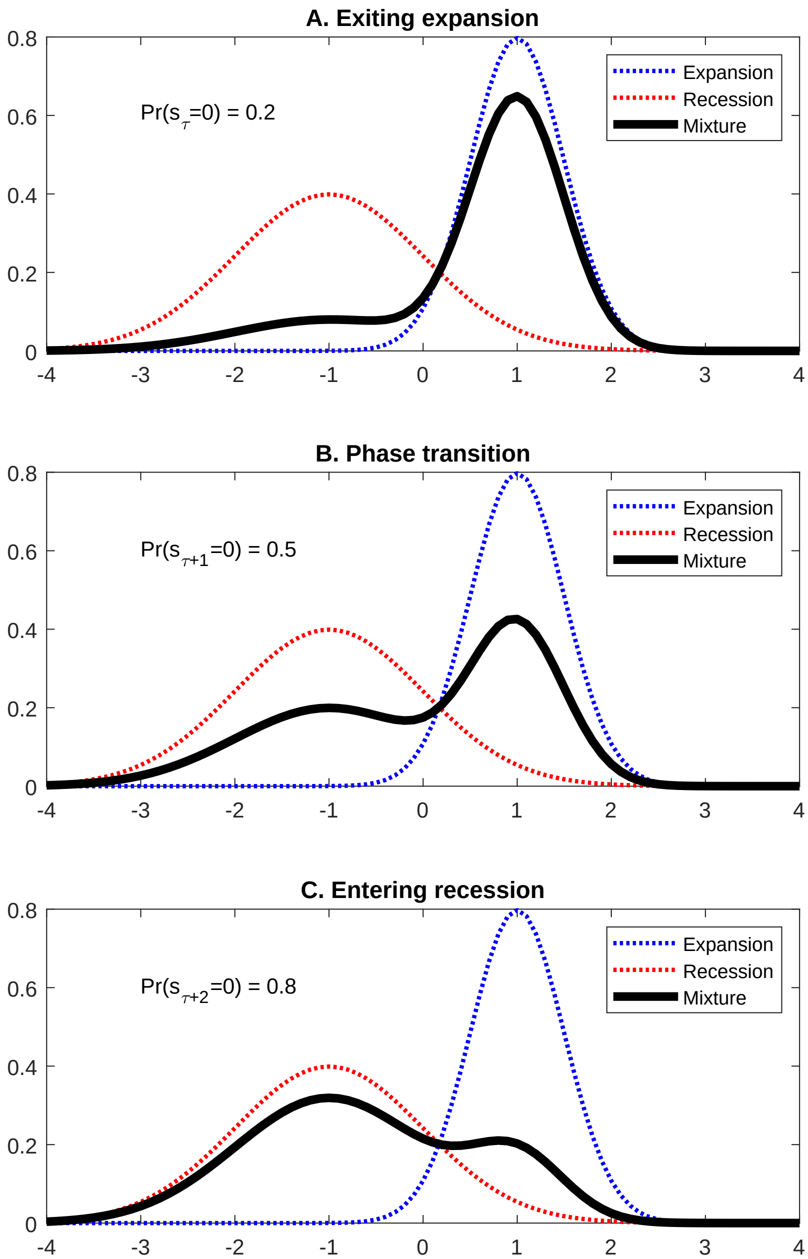
Note. Cyan bars denote real GDP annual growth of Latin America and the Caribbean from the World Bank. The sample covers the period 2007:07-2021:05.

Figure 21: Distribution of the Latin American Momentum Index over time



Note. The figure plots the real-time kernels of the LAMI posterior densities for all the months in the sample 2007:07-2021:05.

Figure 22: Evolution of a mixture of densities around a turning point



Note. The figure illustrates how a mixture of two densities evolves as the weights for each density, defined by the probability of recession, change over time. The dotted blue line draws the density of the growth rate of an economy during expansion, defined by a normal distribution with $\mu = 1$ and $\sigma = 0.5$. The dotted red line draws the density of the growth rate of an economy during recession, defined by a normal distribution with $\mu = -1$ and $\sigma = 1$. The solid black line draws the resulting mixture of the two densities, defined by the recession probability $Pr(s_t = 0)$ as weight.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