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The COVID-19 Economic Crisis in Mexico through the Lens of a Financial Conditions Index

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Abstract

The COVID-19 pandemic not only generated real shocks affecting economic activity severely, but also a broad uncertainty that unleashed an extreme shock to financial markets. In this paper, we focus on the financial dimension of the pandemic from the viewpoint of an emerging market economy. Accordingly, we estimate a financial conditions index for Mexico since 1993 and find that the acute turmoil generated by the pandemic stands among the four largest episodes of financial distress experienced by the country. In addition, we find evidence suggesting that real variables have responded differently to shocks that worsen financial conditions than to shocks that improve them.

Keywords: COVID-19, financial conditions, impulse responses, local projections.

JEL Classification: C11; C32; E44; G01.

Introduction

The COVID-19 pandemic has severely affected the global economy, with widespread effects both on real activity and financial markets. The uncertainty surrounding the evolution of the pandemic, even with the slow deployment of the vaccination campaign in 2021, still poses unprecedented challenges for policymakers. At the start of the pandemic in early 2020, three macroeconomic shocks hit the global economy. First, as different countries implemented contention measures, value chains were disrupted, wreaking a supply shock that slowly tempered over time. Second, when said measures became stricter, a great lockdown took over common-day activities, plummeting aggregate demand as households shifted resources from consumption to savings. Part of this shift responded to precautionary reasons. Yet, another important driver was consumers' inability to spend in sectors where operations were restricted, such as leisure services. And third, as all of these events were unfolding, uncertainty skyrocketed, risk aversion increased dramatically, and asset prices reacted accordingly, effectively unleashing a financial shock. As a result, stock markets collapsed, the currencies of emerging market economies (EMEs) depreciated importantly, long-term interest rates jumped as a result of higher term-premia, corporate security markets dried up, EMEs sovereign-bond risk premia surged, etc. In sum, by mid 2020, financial conditions reached a substantial deterioration, imposing an additional constraint to aggregate demand and the economic recovery.

In such a complex scenario, attempts to measure the economic impact of the pandemic help policymakers to take appropriate actions. In this regard, in this paper we focus on the financial dimension of the COVID-19 pandemic. In particular, we measure the degree by which financial conditions in Mexico deteriorated as a result of the financial shock generated by the global health crisis, and compare this episode to previous ones of extreme financial distress. Afterwards, we estimate the effects of tighter financial conditions on Mexican economic activity. This exercise sheds light on the effect that a deterioration in financial conditions may have on economic activity in an EME.

To characterize the evolution of financial markets over time in Mexico, we build a financial conditions index (hereafter *FCI*) from June 4 1993 to April 2 2021, at a weekly basis. To do so, we estimate a state-space model through Bayesian methods using a set of financial and economic indicators. Similar to other EMEs, some of these indicators in Mexico became available after the beginning of our sample, as domestic financial markets developed and reached a higher degree of complexity. As such, we adapt our estimation technique to cope with the presence of missing values, which allows us to extend the sample well into the nineties. In addition, we disentangle the estimated *FCI* into a global factor and a domestic or idiosyncratic factor, which permits to investigate the role that both of these components played in different episodes of financial distress. Finally, we quantify the effects of an exogenous shock to *FCI* on real activity through local projections (following the method of Jordà, 2005). An advantage of this method is that we can test directly for the presence of asymmetric effects on the responses of real activity to an easing or a tightening shock to financial conditions.

Our results are the following. We find that the acute tightening of financial conditions generated by the COVID-19 Pandemic Crisis is comparable to that observed during the 1995 Tequila Crisis, the 1998 Russian Crisis, and the 2008 Global Financial Crisis. Nonetheless, in the current episode, financial conditions seemed to have improved somewhat faster than in these previous episodes. According to our estimations, the extreme financial distress caused by the pandemic lasted 51 weeks, a figure almost three times lower than the duration of the extreme distress generated by the Tequila Crisis, which extended for 146 weeks. In addition, the peak deterioration in financial markets during the pandemic happened by the end of May 2020, reaching a maximum of 2.8 standard deviations above trend. In comparison, the peak deterioration of *FCI* during the Global Financial Crisis attained a level of 3.3 standard deviations above trend in the last week of March 2009. Further, in contrast to other episodes, both global and domestic factors played a role in the deterioration of financial conditions during the COVID-19 pandemic. These dynamics contrast with other episodes, in which either the domestic factor was the dominant (as in the Tequila Crisis), or the global factor was (as in the Global Financial Crisis).

In addition, we find that after an exogenous deterioration in financial conditions in Mexico, output, consumption, and investment fall in a hump-shaped pattern for about a year. As one would expect, investment responses are twice as large as those of output and consumption.[1] Furthermore, we find evidence suggesting the presence of asymmetries in the responses of real variables to a shock to financial conditions. Notably, a sudden tightening in financial conditions has a larger effect on the real sector than an unanticipated easing in financial conditions.

This paper relates to different strands in the literature. On the one hand, there is a large body of empirical work on the construction of financial conditions indices and their usefulness to provide early information about future economic performance. Proposed methodologies range from principal component analysis (Hatzius et al., 2010; Gaglianone and Areosa, 2017; Armendáriz and Ramírez, 2017; Prasad et al., 2019; Wang and Li, 2021) to more elaborated estimations that involve vector autoregression (VAR) models and dynamic factor models (Koop and Korobilis, 2014; Hatzius and Stehn, 2018). Our methodology to compute a *FCI* for Mexico belongs to the second group. We complement previous analyses as we focus on an EME, where research is relatively scant. In the case of Mexico, our estimated *FCI* displays similar dynamics than the measure proposed by Armendáriz and Ramírez (2017) for the common sample period. Their measure covers the period April 2004 to August 2016 at a monthly basis. In contrast, our estimate features a longer time span and a weekly frequency, characteristics that allow us to compare a wider set of extreme financial distress episodes, with more granularity regarding the timing of shocks. Moreover, we broaden the scope of analysis by estimating and testing for the presence of asymmetric effects of an exogenous shock to financial conditions on real activity in Mexico.[2]

Following on the latter, our work is also related to the analyses of Fornari and Stracca (2012), Jordà et al. (2013), Abbate et al. (2016), and Hatzius and Stehn (2018). As these authors, we compute the responses of macro variables to financial shocks, and find that real activity is considerably affected. In addition, in line with Mittnik and Semmler (2013) and Prieto et al. (2016), we find evidence supporting the hypothesis that a worsening and an improvement of financial conditions affect differently the economy. Finally, our analysis contributes to an increasing strand of the literature concerned with measuring the economic costs of the COVID-19 pandemic, as carried out by Baker et al. (2020), Jordà et al. (2020), Kohlscheen et al. (2020), Ma et al. (2020), and others. In the context of these papers, our contribution is to provide evidence from the point of view of an EME facing a tightening of financial conditions.

The remainder of the paper is organized as follows. Section 2 describes the methodology and the data used in the estimation of a financial conditions index for Mexico. Section 3 presents the estimated index. Section 4 centers on the unfolding of the COVID-19 Pandemic Crisis and compares the financial consequences of this episode with other episodes of extreme financial distress. Section 5 presents the local-projection framework to compute the responses of selected real variables to a shock to financial conditions, either a tightening or an easing shock. Section 6 concludes.

1 As pointed out by a referee, when computing impulse responses through local projections, one needs to make sure that the shock of interest is orthogonal to innovations affecting the dependent variable in each of the estimating equations. As explained in Section 5, we follow a recursive identification strategy to ensure that the shock to financial conditions is, by construction, orthogonal to other shocks affecting economic activity. In addition, we follow closely Jordà (2005)'s methodology to ensure that the estimates of the local-projection coefficients are not subject to endogeneity bias.

2 *Banco de México*'s Financial Stability Report of December 2019 introduced a financial conditions index for Mexico computed through a Factor-Augmented VAR model as in Koop and Korobilis (2014) at a monthly basis, starting in January 2005. Within the common sample, our results are consistent with this index too, attaining a correlation of 87%. As such, the messages provided by the indices regarding financial conditions are very similar for the common sample. Our contribution is thus to extend the observation period and increase its frequency to a weekly basis.

Measuring Financial Conditions in Mexico

We compute a financial conditions index for Mexico (*FCI*) following a methodology similar to those proposed by Hatzius et al. (2010) and Koop and Korobilis (2014). In particular, we estimate a dynamic factor model using a Kalman filter adjusted for the presence of missing values and unbalanced sample availability for the variables included in the model. The estimation spans from June 4 1993 to April 2 2021, at a weekly basis, using 19 different variables, which are described in detail in Table 1. These variables belong to seven different categories: *foreign exchange*, *stocks*, *debt*, *uncertainty*, *country risk*, *commodity prices*, and *economic activity*. These categories are also considered by Hatzius et al. and Koop and Korobilis.[3] Next, we present the dynamic factor model, then we describe the model variables, and finally we propose a decomposition of the *FCI* into its global and domestic components.

The dynamic factor model

The financial conditions index is derived from a single unobservable common factor that partially drives the dynamics of a group of financial and survey-based indicators. The state-space representation of the dynamic factor model is:

$$Y_t = AX_t + Hf_t + w_t \tag{2.1}$$

$$f_t = f_{t-1} + v_t \tag{2.2}$$

where Y_t is an $n \times 1$ vector of financial and survey-based indicators, X_t is an $m \times 1$ vector of current indicators of economic activity, f_t is a single common latent factor, w_t is an $n \times 1$ vector of zero-mean Gaussian innovations with a variance-covariance matrix given by R, and v_t is a zero-mean Gaussian innovation with variance given by the scalar Q. In turn, A is an $n \times m$ matrix of estimated coefficients, and H is an $n \times 1$ vector of factor loadings. Notice that the loading vector H, which is exactly identified, maps how the evolution of the single factor f_t determines part of the observed dynamics of Y_t.[4]

The classical approach to estimate state-space models such as (2.1)-(2.2) is through maximum likelihood. However, this method becomes computationally cumbersome when a large set of equations is involved (see Blake and Mumtaz, 2017). In our case, there is a total of 18 equations in the state-space model, from which 17 are observation equations and 1 is the transition equation of the single latent factor. In such a setting, Bayesian methods offer a computational advantage for two reasons. First, they moderate the well-known pileup problem of maximum likelihood.[5] And second, a linear model, such as ours, can be estimated through Markov chain Monte Carlo (MCMC) iterations from the posterior distribution of the estimating parameters. As such, we use a Gibbs sampler conditional on prior distributions for A, H, f_t, R and Q, and perform MCMC iterations until we achieve convergence for the moments of the joint posterior distribution of these objects. We discuss in detail the estimating algorithm in Section C of the Appendix.

3 These authors also include a category with credit quantities, such as bank loans and insurance disposals. We decided not to include these variables in our estimation because they normally answer to shocks with a lag and depend to a great extent on economic activity.

4 Similar to Hatzius et al. (2010) and Koop and Korobilis (2014), the aim of introducing vector X_t into the model is to purge f_t from the effect of current economic activity. Nonetheless, f_t might still reflect expectations about future macro variables, as asset prices react immediately to news. As noticed by Koop and Korobilis, this is an issue common to all *FCI*s. Therefore, as a robustness exercise, in Section E of the Appendix we show estimations where we substitute the indicators of current economic activity for their short-term forecasts. We also consider an alternative model where vector X_t is excluded all together. The results from these exercises are similar to our benchmark findings, which suggests that the effect of economic activity on f_t is moderated.

5 In the context of model (2.1)-(2.2), the pileup effect of maximum likelihood will tend to estimate Q to be precisely 0 with a finite probability. See Stock (1986) for further details.

Finally, in EMEs is common to find short and uneven samples for financial variables. This is due to a lag in the development of certain markets, such as long-term fixed-income assets or complex derivatives, as opposed to more liquid markets, such as short-term government bonds or forward FX contracts. This caveat limits the estimation of a *FCI* through popular approaches (e.g., principal component analysis), since the sample for which all variables of interest are available is short. In contrast, a Kalman filter approach allows to expand the estimating sample by using all the available information in any given period. In Section D of the Appendix we show how to adjust the state-space representation of the model to accommodate the presence of missing values.

Sample description

We consider 17 financial and survey-based variables covering a wide range of categories. In addition, we also include two indicators for current economic activity: Mexico's Global Economic Activity Index (IGAE, by its Spanish acronym), and the U.S. Industrial Production Index (IPI). Table 1 describes in detail the complete data set.

Financial conditions indices are usually presented at a monthly basis. However, given our particular interest in tracking financial strains in Mexico as the COVID-19 pandemic evolved, we estimate it weekly.[6] Most of the financial variables described in Table 1 are included as end-of week figures. However, there are some exceptions. For instance, we measure the volatility of the FX and the Mexican stock market using the weekly standard deviation of the peso-dollar exchange rate and the Mexican stock-price index. Also, we assume that monthly data is observable at the end of each month. Among these data are the sentiment indicators from Banco de México's *Survey on the Expectations of Private-Sector Economic Specialists* (Banxico's SES, for short). Finally, vector X_t repeats the current monthly figures of IGAE and IPI over the weeks within the corresponding month.

Table 1. Data Description

Category	Series	Definition	Sample	Source
Variables contained in vector Y_t				
FX market	*ER*	Fix rate, Pesos per US Dollar, end of week	1993:M3-2021:M4	Banxico
	σ^{ER}	Volatility of *ER*, weekly standard deviation	1993:M3-2021:M4	Own calculation
Stock market	*IPC*	Log of the Mexican Stock Exchange Index, end of week	1993:M3-2021:M4	Grupo BMV
	σ^{IPC}	Volatility of the log-difference of IPC, weekly st. dev.	1993:M3-2021:M4	Own calculation
	*SP*500	S&P 500 Stock Price Index, end of week	1993:M3-2021:M4	Bloomberg

6 The Federal Reserve Bank of Chicago also releases a weekly update of its National Financial Conditions Index (NFCI).

Table 1 (continued). Data Description

Category	Series	Definition	Sample	Source
		Variables contained in vector Y_t		
Debt market	$IR^{MX:10y3m}$	10 year-3 month Gov. bond spread, Mexico, end of week	2001:M12-2021:M4	Valmer & Banxico
	$IR^{MX:10y2y}$	10 year-2 year Gov. bond spread, Mexico, end of week	2001:M12-2021:M4	Valmer & Banxico
	$IR^{US:10y3m}$	10 year-3 month Treasury bond spread, US, end of week	1993:M3-2021:M4	FRED
	$IR^{US:10y2y}$	10 year-2 year Treasury bond spread, US, end of week	1993:M3-2021:M4	FRED
Uncertainty	*EUNC*	Uncertainty about Mexico's economic situation, monthly	1999:M1-2021:M4	Banxico's SES
	PUNC	Uncertainty about Mexico's economic policy, monthly	1999:M1-2021:M4	Banxico's SES
	ICLIM	Deterioration in investment climate, monthly	1999:M1-2021:M4	Banxico's SES
	VIX	VIX index, US, end of week	1993:M3-2021:M4	Bloomberg
	EPU^{US}	Economic Policy Uncertainty Index, US, monthly average	1993:M3-2021:M4	FRED
Country risk	$EMBI^{W}$	Common factor of EMBI plus spread for selected countries	1997:M9-2021:M4	Own calculation with data from JP Morgan
	$EMBI^{MX}$	Idiosyncratic factor of Mexico's EMBI plus spread	1997:M9-2021:M4	
Commodities	*OIL*	Brent crude price, end of week.	1993:M3-2021:M4	Bloomberg
		Control variables contained in vector X_t		
Economic activity	*IGAE*	Global Economic Activity Index, Mexico, monthly	1993:M3-2021:M3	INEGI
	IPI^{US}	US Industrial Production Index, US, monthly	1993:M3-2021:M3	FRED

Note: See Appendix, Section B, for further details on the computation of Mexican government-bond yields and Mexico's idiosyncratic country risk. Banxico's SES stands for Banco de México's *Survey on the Expectations of Private-Sector Economic Specialists*.

To induce stationarity into the model, we take the quarterly growth rates of all level variables, such as FX, stock-market price indices, and economic-activity variables, computed as 12-week log-differences. For variables in basis or percentage points, such as Banxico's SES indicators, sovereign-risk spreads, or bond yields, we use 12-week simple differences. In addition, we standardize all variables to account for their specific measurement unit.[7]

Decomposing FCI into global and domestic factors

Prasad et al. (2019) stress the importance of including foreign financial variables when estimating a *FCI* for EMEs. The reason is that foreign variables help to proxy potential restrictions that agents in these economies may face to obtain funding from abroad. Following this idea, we approximate the effect of global and domestic factors on the evolution of financial conditions in Mexico using the following time-varying identity and transition equation:

$$\hat{f}_t = Y_t' \beta_t, \tag{2.3}$$

$$\beta_t = \beta_{t-1} + \Delta_t, \tag{2.4}$$

where $\hat{f}_t$ corresponds to the median estimate of f_t from model (2.1)-(2.2), Y_t is the same vector of financial variables specified in that model, β_t is an $n \times 1$ time-varying vector of weights, and Δ_t is an $n \times 1$ vector capturing changes in these weights over time. To compute β_t, we consider a state-space model where (2.3) is the observation equation and (2.4) is the transition equation. As such, an estimate of β_t results from a simple Kalman filter. We interpret this vector of weights as a map of how changes in Y_t translate into changes of $\hat{f}_t$ at every period $\boldsymbol{t}$. Notice that this interpretation differs from the one offered for the factor loadings H in (2.1), where the mapping goes the other way around and is not time-varying. Instead, β_t are reduced-form coefficients that help to provide intuition about what variables contain clearer signals regarding changes in financial conditions.

Now, consider the partition of Y_t into global and domestic factors, such that $Y_t = \left\{Y_t^{g\mathrm{T}}, Y_t^{d\mathrm{T}}\right\}^{\mathrm{T}}$ and $\beta_t = \{\gamma_t^{\mathrm{T}}, \delta_t^{\mathrm{T}}\}^{\mathrm{T}}$. As such, $\hat{f}_t = g_t + d_t$, where the global and domestic components are given by $g_t = Y_t^{g\,\mathrm{T}} \gamma_t$ and $d_t = Y_t^{d\,\mathrm{T}} \delta_t$, respectively. The variables considered in the global partition Y_t^g are $SP500_t$, $IR_t^{US:10y3m}$, $IR_t^{US:10y2y}$, VIX_t, EPU_t^{US}, $EMBI_t^W$ and OIL_t, while the remainder are included in the domestic partition Y_t^d.[8]

The estimated FCI

Trend and cycle components of financial conditions

We estimate model (2.1)-(2.2) through 600,000 iterations of the Gibbs sampler presented in Section C of the Appendix. Out of these iterations, we retain the last 60,000 draws and, in order to avoid correlation among them, we keep one draw out of every 60. As such, from the remaining 1,000 draws, we compute the median of f_t at each point in time, i.e. $\hat{f}_t$. We interpret this estimate as weekly changes in financial conditions in Mexico. An increase in this variable denotes a deterioration, while a decrease signals an improvement. Thus, by accumulating $\hat{f}_t$ forward, we measure how financial conditions have changed over time in Mexico. Let this accumulated measure be defined as

7 We opt for 12-week differences in order to moderate the noise that the week-to-week volatility of asset prices may bring into the model.

8 We are aware of the fact that domestic variables reflect, up to a certain degree, financial conditions abroad. However, the proposed decomposition is pedagogically helpful to illustrate how changes in Mexico's financial conditions result from changes in variables more related to either idiosyncratic factors or global factors.

$$F_t = \sum_{i=0}^{t} \widehat{f_i}$$

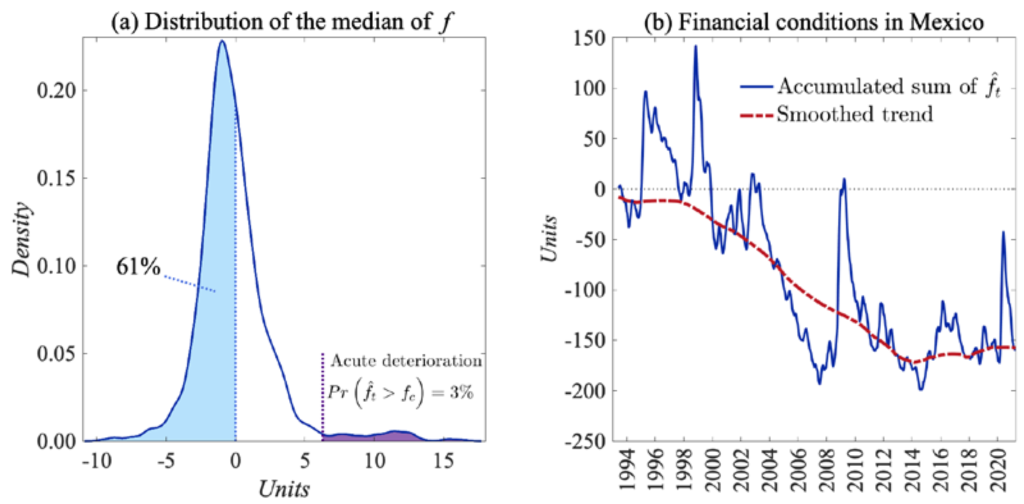
Panel (a) of Figure 1 shows the distribution of the 1,453 weekly estimates of $\hat{f}_t$. It is noteworthy that more than 60% of those weekly numbers are lower than zero. In addition, the distribution displays a fat tail on the right, featuring weeks with the top 3% of acute deteriorations in financial conditions, that is at least 2.3 standard deviations above the mean. Panel (b) displays in turn F_t, which follows a negative trend for the most part of the sample period. Thus, our results suggest that, despite certain episodes of acute distress, financial conditions in Mexico have improved in general since the mid-90s. Likely determinants of this trend are a more sophisticated and resilient financial system, deeper markets, greater liquidity, among other factors.

In order to focus on the cyclical properties of financial conditions, we need to remove their long-term trend. To such end, we estimate the following trend regression with time-varying coefficients and stochastic volatility:

$$F_t = b_{0,t} + b_{1,t} \log t + e^{\frac{h_t}{2}} \varepsilon_t, \qquad (3.1)$$

where the error term ε_t is a zero-mean Gaussian innovation with a variance equal to 1, while the log-volatility term h_t evolves according to the random walk process $h_t = h_{t-1} + \nu_t$, with ν_t being also a zero-mean Gaussian innovation, but with variance equal to ω^2. We estimate this equation through Bayesian techniques.[9] Then, we obtain a smoothed fitted value for the trend component of F_t, which we show as the dashed line in panel (b) of Figure 1. The trend component of financial conditions displays a monotonic downward trajectory from the end of 1990s to mid 2014.[10]

Figure 1. Estimates of Weekly Changes in Financial Conditions and their Trend

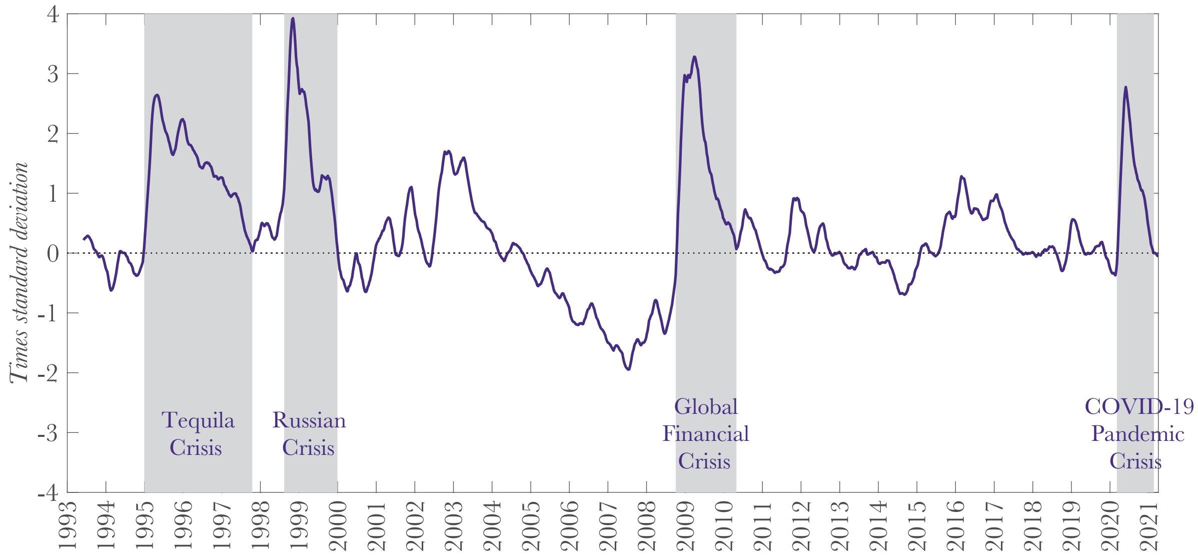


Note: Panel (a) shows the density distribution of the median of the common factor f_t, i.e. $\hat{f}_t$, as estimated in (2.1)-(2.2). Further, f_c denotes a constant such that realizations of $\hat{f}_t$ above that level belong to the top 3% of all weekly estimates for this variable, i.e. $\Pr(\hat{f}_t > f_c) = 3\%$. Panel (b) displays the accumulated sum of $\hat{f}_t$ through time, along with a trend component that results from the following regression: $F_t = b_{0,t} + b_{1,t} \log t + e^{h_t/2}\varepsilon_t$, where $h_t = h_{t-1} + \nu_t$, $\varepsilon_t \sim \mathcal{N}(0,1)$, and $\nu \sim \mathcal{N}(0,\omega^2)$. This equation is estimated through Bayesian techniques.

9 See chapter 11.3 of Kroese and Chan (2014) for the estimation details of stochastic volatility models.

10 An alternative trend estimator is the well-known Hodrick-Prescott (HP) filter. However, as Hamilton (2018) argues, this filter may produce spurious dynamic relations that have no basis in the underlying data-generating process. In addition, the HP filter lacks from a mechanism that isolates its fitted value from bouts of volatility that are more related to the cyclical component of a variable. Indeed, these bouts may bias the estimated trend component of a series, since the weight of any data point is the same. In contrast, the trend regression proposed in equation (3.1) is designed to reduce the weight of information stemming from periods showing an unusually high volatility.

Figure 2. Financial Conditions Index at a Weekly Basis



Note: The index is computed in four steps. First, we compute the median for each of the weekly changes of f_t, namely $\hat{f}_t$. Second, we compute its accumulated value through time, so that $F_t = \sum_{i=0}^{t} \hat{f}_i$. Third, we compute the trend component of F_t by estimating equation (3.1). Finally, we standardize the difference between F_t and its trend, as stated in equation (3.2).

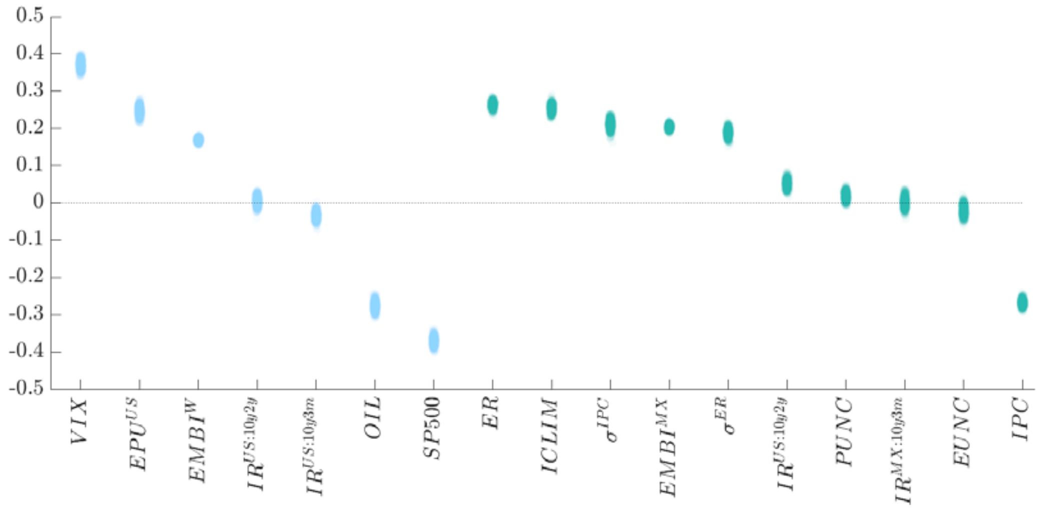
Finally, the financial conditions index results from the standardized difference between F_t and its trend, i.e.

$$FCI_t = \Gamma_t / var(\Gamma_t)^{\frac{1}{2}}, \tag{3.2}$$

where $\Gamma_t = F_t - b_{0,t} - b_{1,t}\log(t)$. Figure 2 displays the *FCI* for Mexico at a weekly basis. The index shows how far, in terms of standard deviations, the cyclical component of financial conditions is from its trend component. Notice that the index accurately captures periods in which financial conditions tightened significantly, such as the 1995 Tequila Crisis, the 1998 Russian Crisis, the 2008 Global Financial Crisis, and the COVID-19 Pandemic Crisis. These episodes are highlighted in the figure with shaded areas. The starting dates of these areas correspond to periods in which median changes in financial conditions displayed an acute deterioration for at least two weeks in a row (see panel (a) in Figure 1). In turn, the end of the shaded areas signals the week when the *FCI* returns to its trend (see Section 4.2 further details).

Figure 3 presents the full set of posterior draws of the estimated factor loadings of vector H in equation (2.1). As mentioned before, these loadings capture the impact of changes in financial conditions on the dynamics of the variables contained in vector Y_t. It is noteworthy that the range of posterior estimates for each element of H is compact. Also, most of the signs of these estimates are quite intuitive. For instance, if financial conditions worsen, the volatility of stock markets and the exchange rate surges (VIX, σ^{IPC}, σ^{ER}), sovereign spreads go up ($EMBI^{W}$, $EMBI^{MX}$), oil prices and stocks market indices fall (*OIL*, *SP*500, *IPC*), the peso depreciates against the dollar (*ER*), the investment climate in Mexico deteriorates (*ICLIM*), and economic policy uncertainty in the U.S. increases (EPU^{US}). In contrast, the results suggest that the effect of changes in financial conditions is somewhat limited for the slope of the yield curve in the U.S. and Mexico (the *IR*-series), and for Mexican analysts' opinion regarding the economic situation (*EUNC*) and economic policy (*PUNC*).

Figure 3. Posterior Distributions of the Factor Loadings H

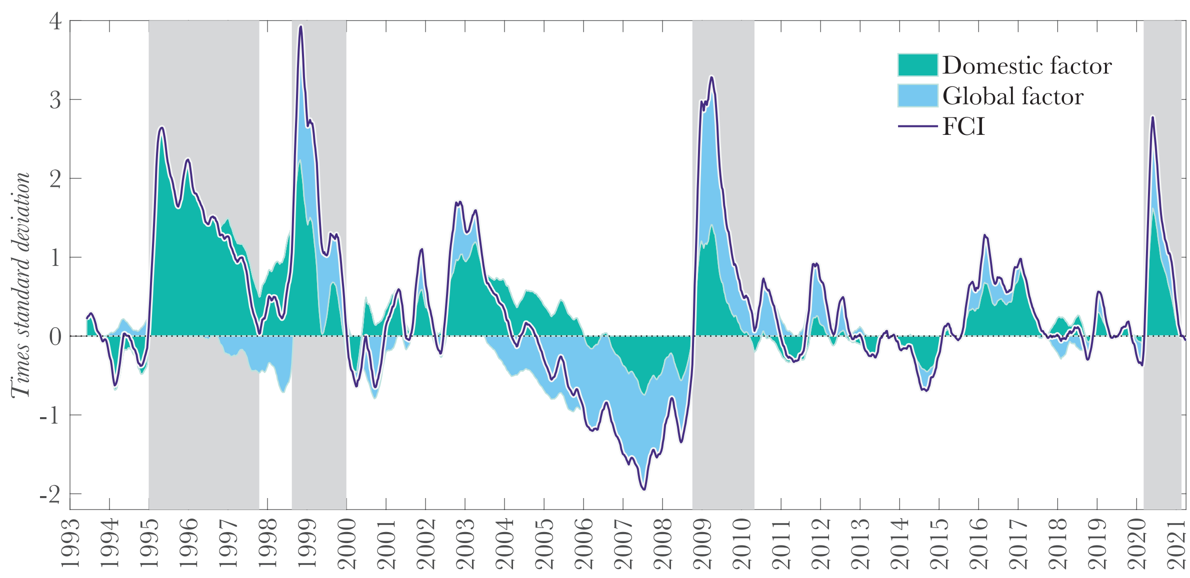


Note: The figure shows the full set of the posterior distribution of vector H for each of the 17 financial and survey-based variables included in the model. Each dot is a draw from the posterior distribution, consisting of 1,000 draws. Global variables are presented first. See Table 1 for a detailed definition for each variable.

Global and domestic factors

As explained in Section 2.3, changes in financial conditions can be triggered by domestic and/or global factors. Similar to the construction of the *FCI*, we accumulate the terms g_t and d_t presented earlier, then we compute their low frequency component, and finally we standardize the difference between the accumulated series and its trend.[11] Figure 4 shows the decomposition of *FCI*. As it stands out, the financial distress generated by the Tequila Crisis was mainly caused by disruptions in domestic markets. In contrast, the other three episodes highlighted in the figure were the result of turmoils in both global and domestic markets, including the acute financial distress related to the COVID-19 pandemic.

Figure 4. Contribution of Domestic and Global Factors to *FCI*

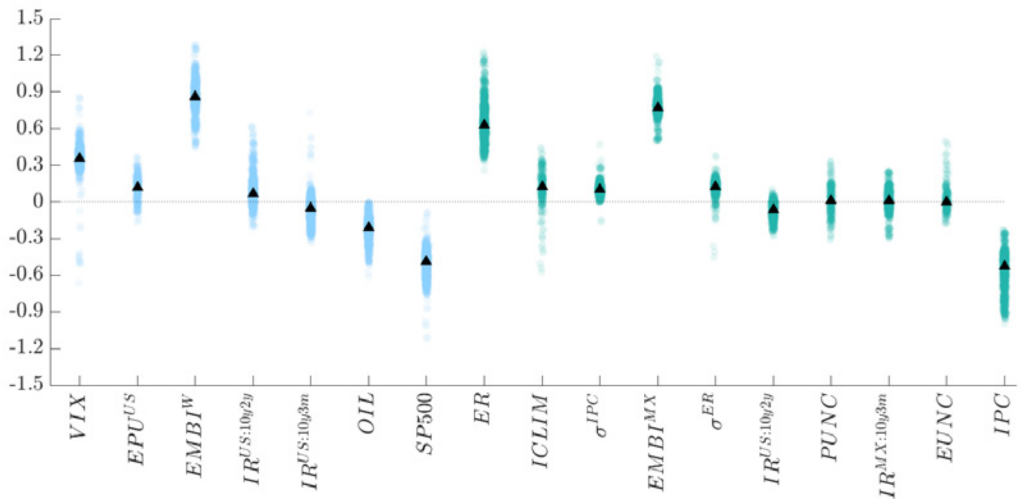


Note: Variables included in the global factor g_t are VIX, EPU^{US}, $EMBI^{W}$, $IR^{US:10y2y}$, $IR^{US:10y3m}$, OIL, and $SP500$. In turn, those included in the domestic factor d_t are ER, σ^{ER}, $ICLIM$, $EMBI^{MX}$, $IR^{MX:10y2y}$, $IR^{MX:10y3m}$, $PUNC$, $EUNC$, IPC, and σ^{IPC}.

11 To ensure that the sum of the cyclical component of the global and domestic factors add up to *FCI*, we compute the trend of the global factor by estimating an equation similar to (3.1). In turn, we compute the low frequency component of the domestic factor as the simple difference between the trends of *FCI* and the global factor. We obtain very similar results if instead we take the domestic factor as the pivot and the global factor as the residual. This is the case because, by construction, the global and domestic factors are co-integrated with *FCI*.

Figure 5 shows the distributions of the weights β_t from equation (2.3). As mentioned earlier, these reduced-form coefficients help to identify which variables offer clearer signals about changes in financial conditions. Contrary to the posterior distributions of the factor loadings H the ranges of the distribution of β_t are wider and crosses the zero line more often. The triangles in the figure show the median of β_t for all of the weeks observed for each variable. As such, an increase in sovereign spreads, an exchange rate depreciation, a rise in stock and exchange-rate volatility, a higher uncertainty regarding U.S. economic policy, and a fall in the prices of oil and stocks signal, most of the times, a clear deterioration of financial conditions. In contrast, changes in other variables might or might not be related to a worsening of financial conditions.

Figure 5. Kalman-Filter Distributions of the Time-Varying Weights β_t



Note: The figure shows the set of Kalman-filter estimates for the weights β_t presented in equation 2.3. Each dot is an estimate for a particular time period in the sample in which a variable in Y_t is observed. The triangles denote the median of β_t for each variable. Global variables are presented first. See Table 1 for a detailed definition of each variable.

The COVID-19 Pandemic Crisis

Three extreme shocks

The COVID-19 pandemic has led to a qualitatively different crisis to those observed in recent years, not only for the gravity of the greatest health emergency seen in a century, but also for the incidence of extreme shocks that paralyzed economic activity and severely worsened financial conditions. In early 2020, as the virus started propagating around the world, different countries adopted production restrictions as an attempt to contain the spread of the virus. This supply shock effectively disrupted supply chains worldwide, generating input scarcity in some industries. Later, as early contention measures proved insufficient, restrictions on aggregate demand followed. Governments around the world implemented widespread social-distancing policies, which included domestic mobility restrictions, shutting down schools and workplaces, closing borders to international traveling, heavily restricting social gatherings, and suspending service sector activities that implied crowding people. As such, a great lockdown took over common day activities, shifting consumer spending towards savings and to sectors less affected by the pandemic. The extreme shocks in aggregate supply and demand took a heavy toll on economic activity in 2020.[12]

Figure 6 presents a quantitative index showing the severity of the COVID-19 contention measures taken by fifteen countries from January 1 2020 to March 30 2021. We built this index

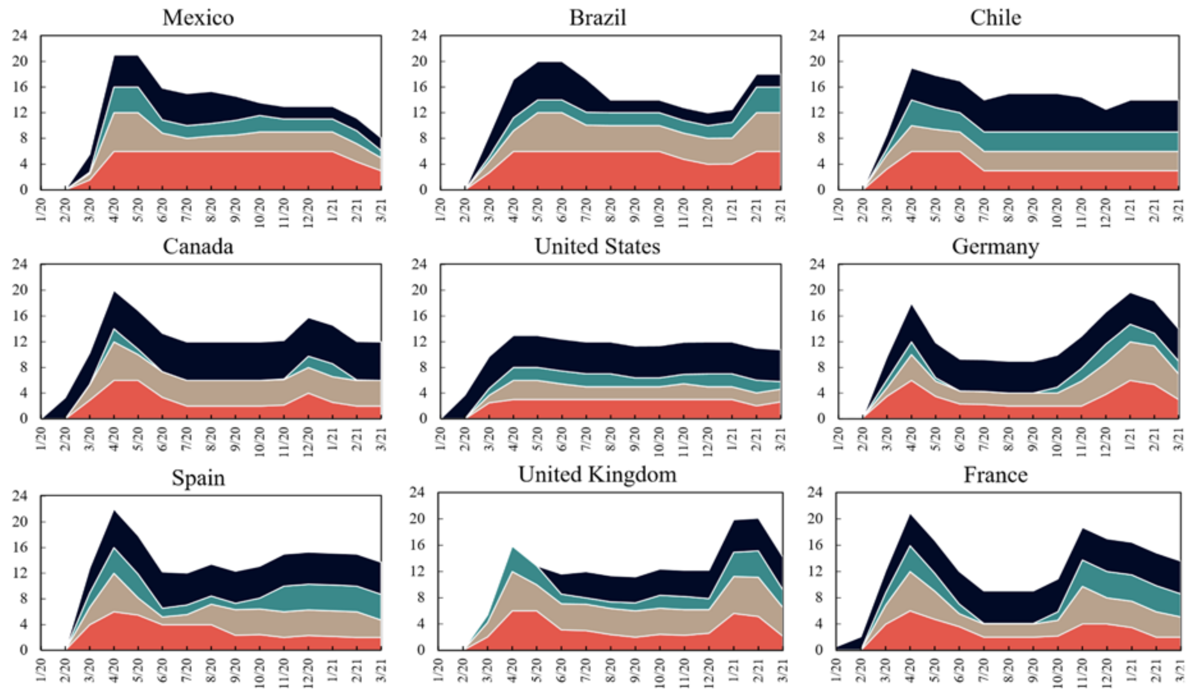
12 In its 2020 annual report, the BIS summarizes how lockdown measures affected both aggregate demand and supply, generating a sudden cutback on spending and obstructing supply chains.

using public information collected daily by Reuters, who clusters the measures into four categories concerning schools, workplaces, stay-at-home, and borders. Reuters also differentiates the measures on the basis of their severity and geographical implementation (i.e., locally or nationwide).[13] It is noteworthy that the first tightening of contention measures took place between March and June 2020. As a result, for the countries shown in Figure 6, with the exception of China, real GDP in 2020Q2 fell dramatically, reaching on average 86% of the level it registered a year earlier.[14]

Figure 6 also shows heterogeneity regarding the intensity and approach taken by different countries to contain the virus. For example, while Mexico and Brazil put more emphasis in the nationwide shut down of schools, Japan and Australia focused more on border controls. In addition, some European countries renewed their restrictions as they were hit by a second wave of contagions in late 2020.

As health and economic authorities battled the spread of the virus, uncertainty loomed in financial markets, risk aversion increased, and investors worldwide abruptly shuffled their portfolios towards safer and more liquid assets. The financial shock generated important capital outflows and a notable exchange rate depreciation in EMEs, along with a generalized asset price volatility in different markets and a fall in oil prices. Figure 7 zooms into the dynamics of *FCI*

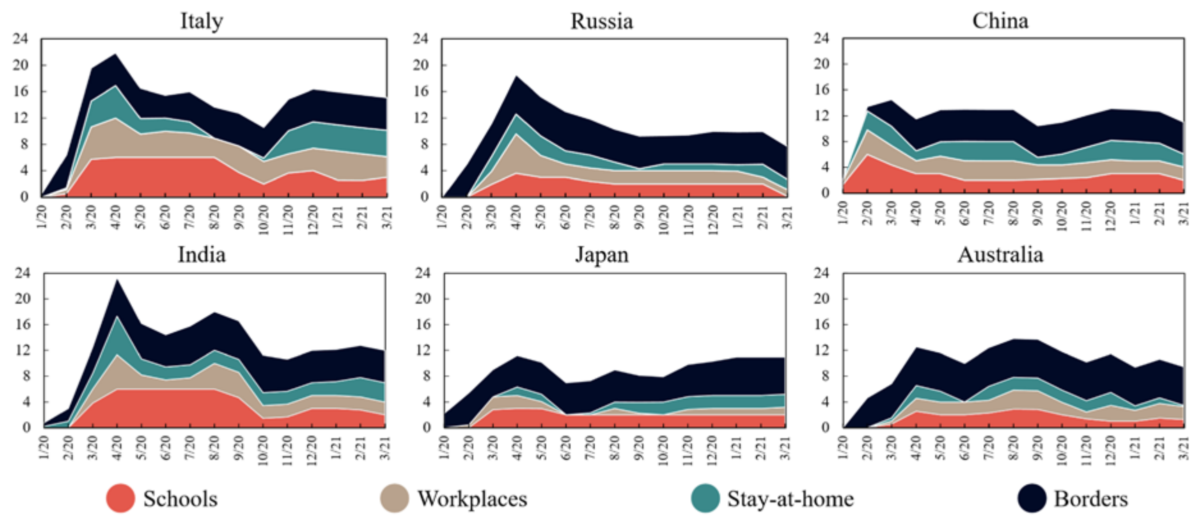
Figure 6. Severity of COVID-19 Contention Measures



13 See Reuters' *COVID-19 Global Tracker* at https://graphics.reuters.com/world-coronavirus-tracker-and-maps and Section A of the Appendix for further details.

14 This number is computed with information from the St. Louis FRED database, using data for real GDP in domestic currency. In the case of China, with data from its National Bureau of Statistics, the largest drop in real activity happened in 2020Q1, when real GDP located at 93% of the level it registered 12 months earlier.

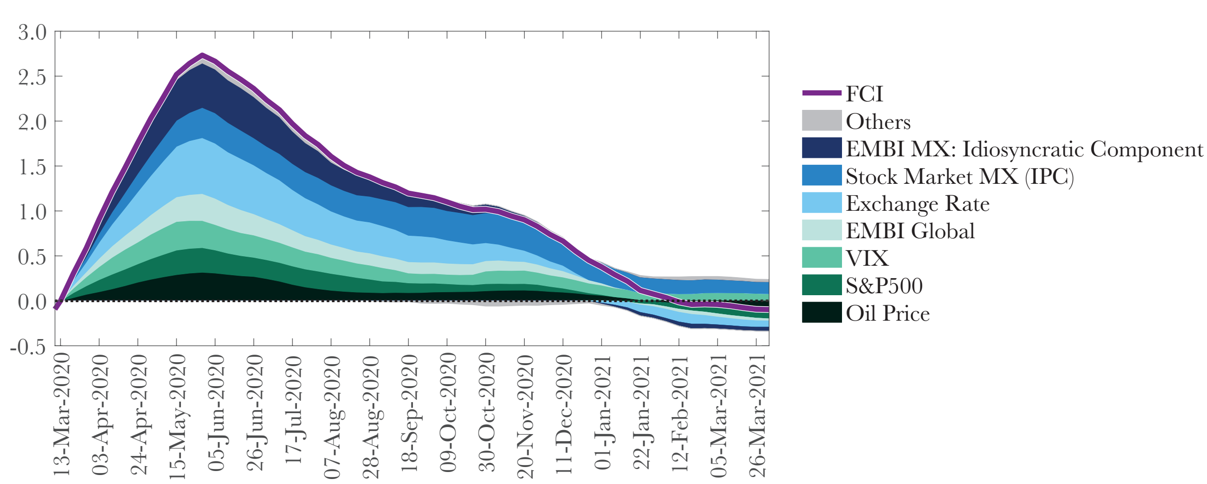
Figure 6 (continued). Severity of COVID-19 Contention Measures



Note: The index was constructed using information from Reuters' *COVID-19 Global Tracker* (https://graphics.reuters.com/world-coronavirus-tracker-and-maps). For details about the construction of the quantitative index shown in the figure, see Section A of the Appendix).

during the pandemic and shows a decomposition of its main contributors following the methodology presented in Section 2.3. Financial conditions in Mexico started to tighten rapidly at the beginning of March 2020, period that coincides with the intensification of the COVID-19 contention measures. The peak of the financial tightening in *FCI* is observed by the end of May 2020, reaching a level of 2.8 standard deviations above its trend. In the same vein, the largest weekly deterioration in financial conditions during this episode was observed in the third week of March 2020, a fluctuation belonging to the top 1% of weekly changes recorded since June 1993. According to our estimations, the main contributors to the *FCI* deterioration were the exchange rate depreciation and the increase in the country's sovereign risk premium, followed by a fall in stock market prices in Mexico and the U.S., a rise in the volatility of the latter, and an increment in the sovereign spreads of other EMEs.

Figure 7. The COVID-19 Pandemic Crisis: Main Contributors to the Financial Shock



Note: The figure shows the contribution of those variables that commonly offer a clear signal about changes in *FCI*. The group *Others* contains the aggregated contribution of the rest of variables.

Financial conditions started to improve gradually since June 2020, following the announcement and implementation of several fiscal and financial aid programs in different advanced and emerging economies. These policies were accompanied by an easing of monetary policy and the deployment of additional measures by central banks, included *Banco de México*.[15] In addition, the emergency use authorization of COVID-19 vaccines by different governments in late 2020 and beginning of 2021 led to an accelerated improvement in financial conditions. In 2021, as the vaccination campaign progressed and contention measures were cautiously lifted, the world economy continued to recover, although with a notable heterogeneity across sectors and countries.

Comparison with respect to other episodes of extreme stress

The COVID-19 pandemic brought about one of the four extreme episodes of financial distress experienced in Mexico in the last thirty years. As highlighted above, the other episodes were the Tequila Crisis, the Russian Crisis, and the Global Financial Crisis. Using our estimates for the weekly changes in *FCI*, we set the starting date of each episode as the period in which $\hat{f}_t$ exhibited levels at the top 3% of its distribution for at least two consecutive weeks (see Figure 1). In turn, we set the ending date of each episode as the week in which *FCI* returned to trend (see Figure 2). According to these criteria, Table 2 presents the corresponding periods of extreme stress in financial conditions in Mexico as measured by *FCI*.

Table 2. Periods of Four Episodes of Extreme Stress According to *FCI*

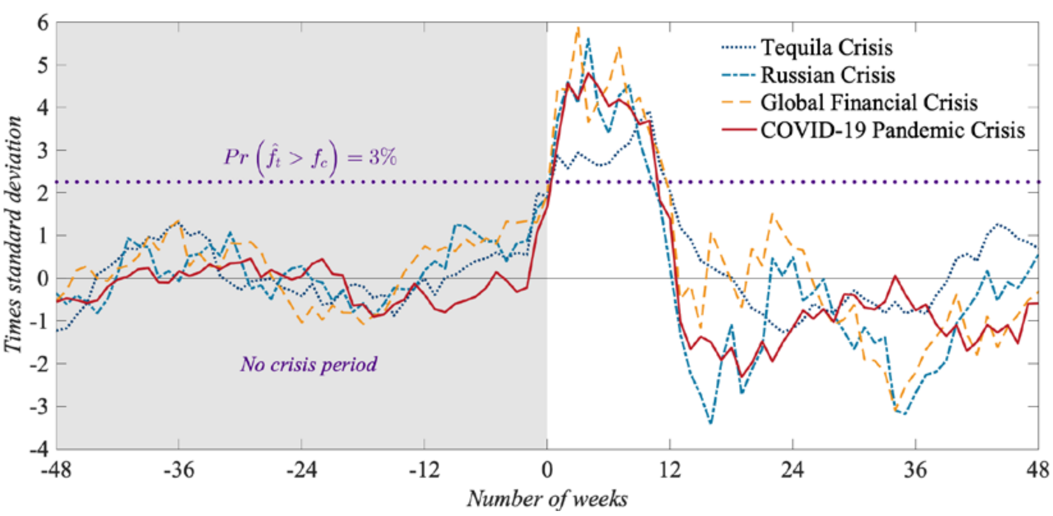
Episode	Starting Period	Ending Period	# Weeks
Tequila Crisis	30 December 1994	10 October 1997	146
Russian Crisis	14 August 1998	24 December 1999	72
Global Financial Crisis	3 October 2008	23 April 2010	82
COVID-19 Pandemic Crisis	6 March 2020	19 February 2021	51

Note: The starting date for each episode corresponds to the period in which at least two consecutive weeks displayed an acute deterioration of financial conditions, i.e. one belonging to the top 3% of the distribution, as shown in panel (a) in Figure 1. The ending date corresponds to the week in which *FCI* returned to trend, as shown in Figure 2.

Panel (a) of Figure 8 shows for the aforementioned episodes the estimates of weekly changes in financial conditions normalized by their standard deviation. The panel presents two periods: before the crisis and during the crisis. In regard to the former, it is noteworthy that $\hat{f}_t$ remains inside an interval of about one standard deviation around zero for most of the weeks before the financial shock. Then, after said shock, the weekly estimates indicate an acute worsening in financial conditions for about ten to twelve weeks, that is, with realizations of $\hat{f}_t$ at the top 3%

Figure 8. Four Episodes of Extreme Stress in Financial Markets

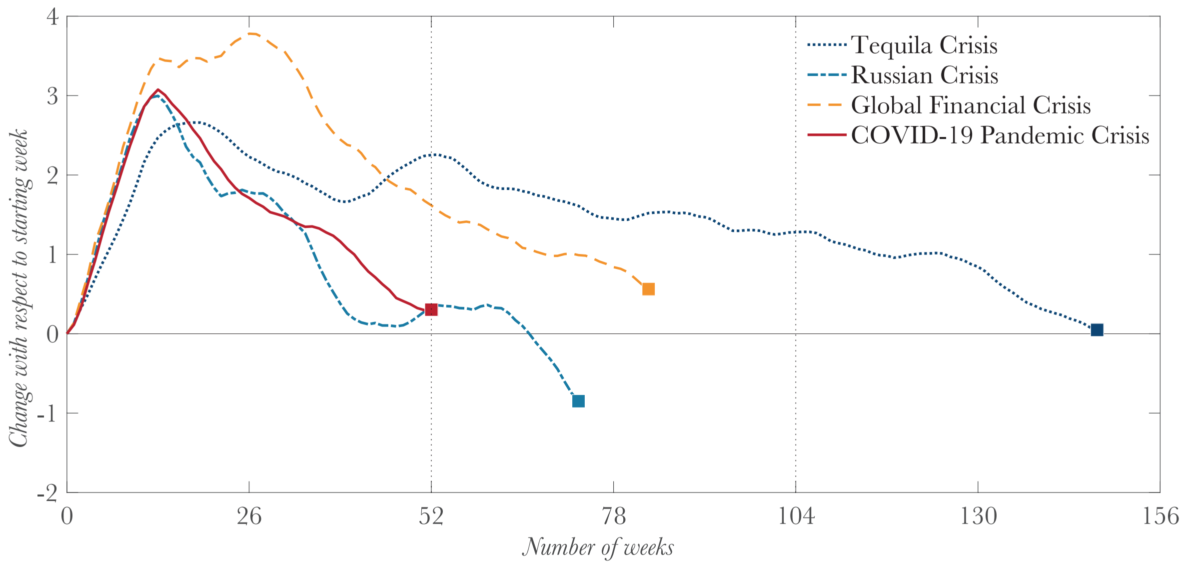
Panel (a): Weekly Estimates of $\hat{f}_t$



15 For further details, see the press releases of *Banco de México* of March 20, 2020, "Measures to Provide MXN and USD Liquidity and to Improve the Functioning of Domestic Markets," and April 21, 2020, "Additional Measures to Foster an Orderly Functioning of Financial Markets, Strengthen the Credit Channels and Provide Liquidity for the Sound Development of the Financial System," as well as the executive summary of its Quarterly Report January-March 2020.

Figure 8 (continued). Four Episodes of Extreme Stress in Financial Markets

Panel (b): *FCI*



Note: See Table 2 for the starting and ending periods of each episode. In panel (a), the weekly changes in financial conditions, indicated by $\hat{f}_t$, are normalized using their standard deviation, which explains the difference with respect to Figure 1. In panel (b), the *FCI* of each crisis episode shows the difference between any given period and the initial crisis period, i.e. $FCI_t - FCI_{t_0}$, where t_0 is week 0 of each crisis episode.

of its distribution.[16] Afterwards, financial conditions display improvements with a notable heterogeneity and volatility across episodes. In turn, panel (b) presents the isolated dynamics of *FCI* for each of the episodes. In particular, the figure shows the difference in the index between time t and the starting week of each episode, denoted by $t = 0$. Notice that this normalization implies that the end point of each crisis does not necessarily crosses the y-axis in the Figure, since FCI_0 could be above or below zero. According to our estimations, the episode with the longest duration is the Tequila crisis, whereas the shortest one is the COVID-19 pandemic crisis, spanning roughly a year. Further, this episode presents a peak deterioration in financial conditions as bad as the Russian crisis. Finally, our estimations suggest that the Global Financial Crisis remains as the episode where financial conditions deteriorated the most, displaying near-maximum levels for several consecutive weeks.

Macroeconomic effects of financial shocks

Overview and setup

Since the Global Financial Crisis, several studies have analyzed the effects of financial shocks on economic activity. For instance, Cerra and Saxena (2008), Reinhart and Rogoff (2009), and Jordà et al. (2013), among others, identify differences between "normal" recessions and those generated by financial shocks, which relate to greater output losses. Further, since financial indicators are high-frequency variables, they have proven to be useful for policymakers as timely warnings about the severity of an economic downturn. In this regard, financial conditions indices are usually included in macroeconomic forecasting models (see, for example, Hatzius et al., 2010; Brave and Butters, 2011; Kliesen et al., 2012; Koop and Korobilis, 2014; Gaglianone and Areosa, 2017). In addition, studies exploring tail risks to economic growth using the Growth-at-Risk methodology find that the predictive power of financial conditions is stronger for risks to the downside than to the upside (see Adrian et al., 2018; Prasad et al., 2019; De Santis and

16 Notice that the length of the period of acute deterioration, varying from 10 to 12 weeks depending on the episode, may be the result of our smoothing decision, by which we chose to take the quarterly growth rates for the set of financial and survey-based variables used to estimate $\hat{f}_t$ (see Section 2.2). In any case, panel (a) of Figure 8 shows clearly that a sudden worsening in financial conditions involves extreme increases in *FCI* that take several months to dissipate.

Van der Veken, 2020; Wang and Li, 2021). This result suggests that there might be asymmetric effects of tightening and easing shocks to financial conditions on real activity.

In this section, we provide further insights on the effects of financial shocks on economic activity. To do so, we adapt the local-projection method introduced by Jordà (2005) to a Bayesian framework. We turn to this approach given its overall simplicity and advantage to identify potential asymmetric responses to shocks, in comparison to other specifications such as VAR models. We estimate the responses of Mexican output, consumption, and investment to a financial-conditions shock. It is worth mentioning that we include U.S. output as a control variable in the local projections, given the importance of external demand for the dynamics of economic activity in Mexico. We estimate two types of models: the *baseline*, where we do not distinguish whether the variables of interest respond to a sudden deterioration or improvement in financial conditions; and the *alternative*, where we allow these responses to feature asymmetric paths after a tightening or an easing shock.

Similar to Jordà (2005), the baseline model for the local projection of a vector of variables z_{t+s} onto a linear space $\left(z_{t-1}, z_{t-2}, \ldots, z_{t-p}\right)^{\mathrm{T}}$ is the following:

$$z_{t+s} = \alpha^{s} + B_1^{s+1} z_{t-1} + B_2^{s+1} z_{t-2} + \cdots + B_p^{s+1} z_{t-p} + e_{t+s}^{s} \qquad (5.1)$$

for $s = 0, 1, 2, \ldots, h$, where z_{t+s} is a $k \times 1$ vector of variables at horizon s, α^{s} is a vector of constants, B_i^{s+1} are matrices of coefficients for each lag i and horizon $s+1$, and e_{t+s}^{s} is a vector of error terms. Accordingly, the impulse responses of z_{t+s} to a structural shock c are given by

$$IR(t, s, c) = B_1^{s} c, \text{for } s = 0, 1, 2, \ldots, h, \qquad (5.2)$$

with the normalization of $B_1^{0} = I$, i.e. the identity matrix.[17] Notice that c is a $k \times 1$ vector containing the responses of z_t to the structural shock of interest at the impact period, when $s = 0$. To compute c, one must rely on a strategy to identify the structural shock. In our case, we use the VAR model that results from setting $s = 0$ in (5.1). In particular, we compute the Cholesky decomposition of the variance-covariance matrix of the reduced-form residuals e_t^{0}, i.e. $\mathrm{E}\left\{e_t^{0} e_t^{0\mathrm{T}}\right\} = \Omega$. To identify an orthogonal shock to financial conditions, we order variables in vector z_t from the most exogenous to the most endogenous. Therefore, we place U.S. output first, Mexican consumption, investment, and output afterwards (in that order), and *FCI* at the end. As such, *FCI* responds on impact to shocks in any of the aforementioned variables, whereas these variables respond with a lag to a shock to financial conditions. Thus, in our case, vector c is the last column of matrix C, where the latter is the lower-triangular Cholesky decomposition of Ω, such that $CC^{\mathrm{T}} = \Omega$.

The alternative model is similar to the baseline, with the exception that we replace *FCI* with the following two variables: $FCI_t^{+} = d_t^{+} \times FCI_t$ and $FCI_t^{-} = d_t^{-} \times FCI_t$, where

$$d_t^{+} = \begin{cases} 1, \text{if } \Delta FCI_t > 0 \\ 0, \text{otherwise,} \end{cases} \text{ and } d_t^{-} = \begin{cases} 1, \text{if } \Delta FCI_t < 0, \\ 0, \text{otherwise.} \end{cases}$$

In the alternative model, we place FCI_t^{+} as the fifth variable in the alternative vector of variables $\tilde{z}_t$, and FCI_t^{-} as the sixth one. As such, the tightening financial-conditions shock is the fifth column of matrix C, which we denote as c^{+}. In turn, the easing financial-conditions shock is

17 It is worth mentioning that estimates of B_i^{s} are not subject to endogeneity bias since, as noticed by Jordà (2005), the residuals e_{t+s}^{s} in (5.1) are a moving average of forecast errors from time t to $t+s$, whereas the regressors are dated $t-1$ to $t-p$. This implies that $\mathrm{E}\{z_{t-i} e_{t+s}^{s\,T}\} = 0$ for $i = 1,2, \ldots, p,$ and $s = 0,1, \ldots, h$. This is indeed the same argument regarding the consistency of coefficient estimates of VAR models.

given by the last column of matrix C, which we call c^{-}. Thus, the impulse responses of vector $\tilde{z}_{t+s}$ to a tightening and an easing shock are given by

$$IR(t,s,c^{+}) = \tilde{B}_1^s c^{+}, \text{ and } IR(t,s,c^{-}) = \tilde{B}_1^s c^{-}, \qquad (5.3)$$

respectively, where $\tilde{B}_1^s$ denotes the coefficient matrix for lag 1 and horizon *s* of the alternative model.

The sample period spans from June 1993 to February 2020, just before the spread of the COVID-19 pandemic in Mexico. We restrict the ending period to avoid the extreme shocks to real activity observed during the pandemic, which may bias our estimated coefficients given their notable magnitude. In all equations we include four lags of vector z_t, although the results hold for models with additional lags. We estimate the local projections at a monthly basis and in terms of percent deviations with respect to trend. As such, we approximate a monthly figure for U.S. output using the Denton method for proportional interpolation, whereas we implement Elizondo (2019)'s state-space model to approximate a monthly figure for Mexican output, which exploits the information contained in the IGAE indicator. For consumption and investment, we use the corresponding monthly indicators provided by INEGI. We also compute the monthly average of *FCI* for this exercise. Finally, the U.S. output gap measure is consistent with the CBO's figure, whereas for Mexican variables we adjust a trend regression similar to (3.1).

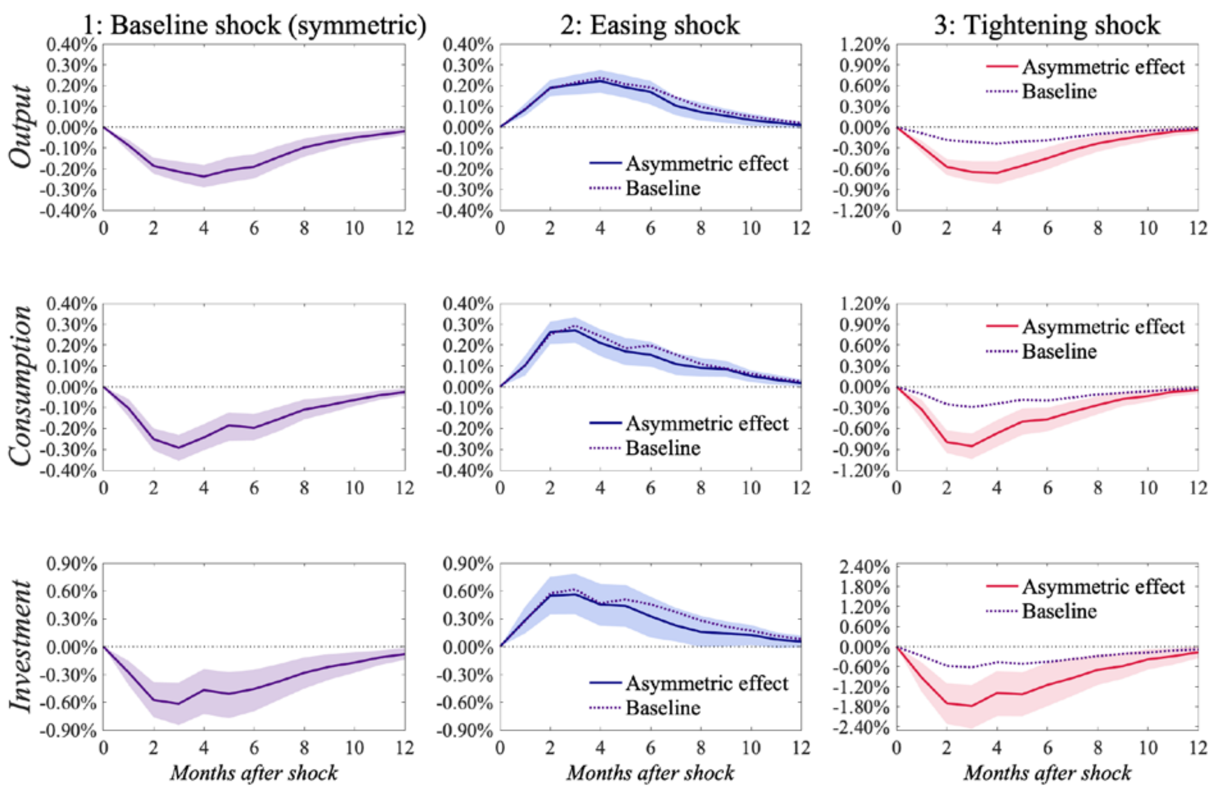
We estimate the baseline and alternative versions of the local projections defined in (5.1) through Bayesian techniques. It is worth noting that, since we are computing impulse responses, we set a strategy for the priors akin to the one used to estimate VAR models. In particular, we set flat priors for matrices B_i^1. Then, as *s* rises, we center the priors at 0 and gradually increase its tightness in a similar way as what it is done with the Minnesota prior.

General responses and asymmetric effects

Figure 9 presents the impulse responses of output, consumption, and investment to a shock to financial conditions. Column 1 shows the symmetric, baseline responses, which are normalized to convey the dynamics of macro variables after a tightening shock. In turn, columns 2 and 3 display the alternative responses, corresponding to either a tightening or an easing shock. According to the baseline estimation, after a sudden deterioration of financial conditions, economic activity declines in a hump-shaped pattern for about twelve months. As one would expect, investment falls more than output and consumption, which is in line with the larger volatility of investment relative to the other two variables. In turn, the responses of output and consumption are of similar magnitude.

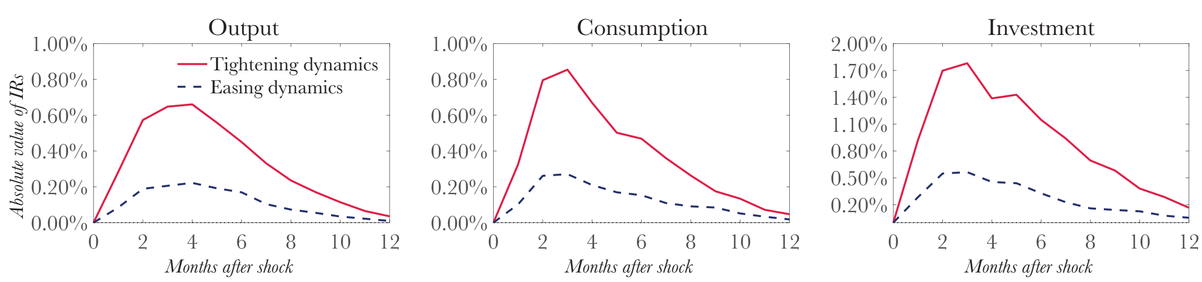
Columns 2 and 3 of Figure 9 reveal the presence of asymmetric effects depending on whether the shock worsens or improves financial conditions. In particular, a tightening shock generates larger responses of real variables in absolute value than an easing shock. In turn, the size of the responses to an easing shock are not statistically different than those generated by a baseline shock. When comparing the absolute value of median responses of real variables to the asymmetric shocks, displayed in Figure 10, it becomes clear that tightening innovations tend to generate responses that are 3 times larger than the responses to easing innovations at the horizon where the maximum effect is reached (i.e., around four months after the shock). In sum, these results are in line with the observation that downside risks to financial conditions seem more important to economic activity than upside risks, at least for the very short term.

Figure 9. Responses of Selected Macro Variables to a Shock to Financial Conditions



Note: The figure shows the median surrounded by a credible interval covering 64% of the posterior distribution of $IR(t,s,c_j)$, where $c_j = c, c^+$, or c^-.

Figure 10. Absolute Value of Asymmetric Median Responses



Note: The figure shows the absolute value of median responses to a tightening and easing shock to financial conditions.

Conclusions

The importance of tracking asset prices as forward-looking indicators of economic activity has been widely acknowledged in the literature. In this sense, financial conditions indices are useful tools to summarize the dynamics of financial markets. Such a tool becomes very handy in the presence of rare events that trigger a widespread uncertainty regarding future economic outcomes. As a result of these events, risk aversion surges, the portfolio composition of investors shifts, and asset prices display a sizable volatility, thus deteriorating financial conditions. The COVID-19 pandemic is one of these rare events.

The financial conditions index for Mexico presented in this paper spans from June 1993 to April 2021, at a weekly basis. We estimated this index through a dynamic factor model based on a Kalman filter that we adjusted to handle missing values and unbalanced data. The relatively long span of our index (for an emerging-market economy) allows us to identify episodes of a similar acute financial tightening. We can therefore compare their evolution, both in terms of severity and duration. We also distinguish the role of domestic and global factors, the latter being particularly relevant for EMEs, on the dynamics of overall financial conditions. Moreover, using local projections, we estimate the responses of output, consumption, and investment to exogenous shocks to financial conditions. This approach allows us to assess the presence of asymmetric effects of said shocks.

Our analysis yields three key findings. First, the financial shock induced by the COVID-19 pandemic remains among the four episodes of extreme financial distress experienced by Mexico in the last thirty years. Nonetheless, this latest episode displays the shortest duration with respect to the previous three. Second, this financial shock was the result of turmoils in both global and domestic markets. In particular, the exchange rate, the sovereign risk premium, and the stock market were the main contributors to the financial shock during this episode. And third, tightening shocks to financial conditions seem to have larger effects on real activity than easing shocks.

Our study has certain limitations. First, we assume that the contribution of the common latent factor (the one summarizing financial conditions) to the evolution of financial variables remains constant over time. This assumption contrasts with the one taken by Koop and Korobilis (2014), who consider a time-varying contribution of the latent factor to financial variables. In the same vein, including stochastic volatility in the model, which is an important feature of the dynamics of financial variables, is likely to improve the accuracy of the financial conditions index. Finally, among potential future extensions of our analysis, remains the evaluation of the effects of shocks to financial conditions on a wider set of relevant macrofinancial variables, such as bank credit, capital flows, and international trade.

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Technical Appendix to "The COVID-19 Economic Crisis in Mexico through the Lens of a Financial Conditions Index"

Severity of COVID-19 contention measures

Through its COVID-19 Global Tracker, Reuters collects daily information about the evolution of the pandemic and the measures implemented to contain it in more than 200 countries. In particular, these measures are gathered in their *lockdown* tracker, which includes four different categories: schools, workplaces, stay-at-home, and borders. Within each category, Reuters

Table A.1. Transformation of Reuters Qualitative Information into a Quantitative Index

Schools		
Levels	Locally	Nationwide
No lockdown measures	0	0
Recommend closing	1	2
Require closing some levels	2	4
Require closing all levels	3	6
Workplaces		
Levels	Locally	Nationwide
No lockdown measures	0	0
Recommend closing	1	2
Require closing some sectors	2	4
Require closing all but essential workers	3	6
Stay-at-home		
Levels	Locally	Nationwide
No lockdown measures	0	0
Recommend not leaving home	1	2
Require not leaving home with some exceptions	2	4
Require not leaving home with few exceptions	3	6
Borders		
Levels		Nationwide
No lockdown measures		0
Screen arrivals		2
Quarantine arrivals from some or all regions		4
Ban arrivals from some regions		5
Ban arrivals from all regions		6

considers different degrees of severity and geographical implementation. However, all information collected by Reuters is qualitative, so there is not a direct relationship about how a combination of different measures translate into an aggregate effort to restrain the pandemic at a country level.

In Table A.1, we propose a simple way to aggregate the information gathered by Reuters. Notice that the categories of school, workplaces, and stay-at-home have four different degrees of severity. We assign a quantitative index from 0 to 3 if the measures were implemented locally

Table A.2. Severity of COVID-19 Containment Measures: Country Indices

	01/20	02/20	03/20	04/20	05/20	06/20	07/20	08/20	09/20	10/20	11/20	12/20	01/21	02/21	03/21
Mexico															
Schools	0.0	0.0	1.5	6.0	6.0	6.0	6.0	6.0	6.0	6.0	6.0	6.0	6.0	4.4	3.0
Workplaces	0.0	0.0	1.0	6.0	6.0	2.8	2.0	2.3	2.5	3.0	3.0	3.0	3.0	2.8	2.0
Stay-at-home	0.0	0.0	0.3	4.0	4.0	2.1	2.0	2.0	2.3	2.6	2.0	2.0	2.0	2.0	1.1
Borders	0.0	0.0	2.8	5.0	5.0	5.0	5.0	5.0	3.8	2.0	2.0	2.0	2.0	2.0	2.0
Total	0.0	0.0	5.5	21.0	21.0	15.9	15.0	15.3	14.6	13.6	13.0	13.0	13.0	11.2	8.1
Brazil															
Schools	0.0	0.0	2.7	6.0	6.0	6.0	6.0	6.0	6.0	6.0	4.8	4.0	4.1	6.0	6.0
Workplaces	0.0	0.0	1.7	3.2	6.0	6.0	4.1	4.0	4.0	4.0	4.0	4.0	4.0	6.0	6.0
Stay-at-home	0.0	0.0	0.8	2.0	2.0	2.0	2.0	2.0	2.0	2.0	2.0	2.0	2.4	4.0	4.0
Borders	0.0	0.0	3.3	6.0	6.0	6.0	5.2	2.0	2.0	2.0	2.0	2.0	2.0	2.0	2.0
Total	0.0	0.0	8.5	17.2	20.0	20.0	17.3	14.0	14.0	14.0	12.8	12.0	12.5	18.0	18.0
Chile															
Schools	0.0	0.0	3.3	6.0	6.0	6.0	3.0	3.0	3.0	3.0	3.0	3.0	3.0	3.0	3.0
Workplaces	0.0	0.0	2.3	4.0	3.4	3.0	3.0	3.0	3.0	3.0	3.0	3.0	3.0	3.0	3.0
Stay-at-home	0.0	0.0	0.9	4.0	3.4	3.0	3.0	3.0	3.0	3.0	3.0	3.0	3.0	3.0	3.0
Borders	0.0	0.0	2.3	5.0	5.0	5.0	5.0	6.0	6.0	6.0	5.5	3.5	5.0	5.0	5.0
Total	0.0	0.0	8.7	19.0	17.8	17.0	14.0	15.0	15.0	15.0	14.5	12.5	14.0	14.0	14.0
Canada															
Schools	0.0	0.0	2.9	6.0	6.0	3.3	2.0	2.0	2.0	2.0	2.1	4.0	2.6	2.0	2.0
Workplaces	0.0	0.0	2.4	6.0	4.0	4.0	4.0	4.0	4.0	4.0	4.0	4.0	4.0	4.0	4.0
Stay-at-home	0.0	0.0	0.1	2.0	0.9	0.0	0.0	0.0	0.0	0.0	0.1	1.8	2.0	0.1	0.0
Borders	0.0	3.3	4.9	6.0	6.0	6.0	6.0	6.0	6.0	6.0	6.0	6.0	6.0	6.0	6.0
Total	0.0	3.3	10.3	20.0	16.9	13.3	12.0	12.0	12.0	12.0	12.2	15.8	14.6	12.1	12.0
United States															
Schools	0.0	0.0	2.5	3.0	3.0	3.0	3.0	3.0	3.0	3.0	3.0	3.0	3.0	2.0	2.6
Workplaces	0.0	0.0	1.2	3.0	3.0	2.4	2.0	2.0	2.0	2.0	2.5	2.0	2.0	2.0	2.0
Stay-at-home	0.0	0.0	1.1	2.0	2.0	2.0	2.0	2.0	1.4	1.4	1.5	2.0	2.0	2.0	1.2
Borders	0.0	3.7	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0
Total	0.0	3.7	9.7	13.0	13.0	12.4	12.0	12.0	11.4	11.4	12.0	12.0	12.0	11.0	10.8
Germany															
Schools	0.0	0.2	3.5	6.0	3.5	2.3	2.3	2.0	2.0	2.0	2.0	3.8	6.0	5.4	3.0
Workplaces	0.0	0.0	1.3	4.0	2.4	2.0	2.0	2.0	2.0	2.0	3.9	4.9	6.0	6.0	4.0
Stay-at-home	0.0	0.0	1.3	2.0	0.5	0.0	0.0	0.0	0.0	0.9	2.0	2.9	2.7	2.0	2.0
Borders	0.0	0.0	3.6	6.0	5.5	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0
Total	0.0	0.2	9.7	18.0	11.9	9.3	9.3	9.0	9.0	9.9	12.9	16.6	19.7	18.4	14.0
Spain															
Schools	0.0	0.0	4.0	6.0	5.5	4.0	4.0	4.0	2.3	2.5	2.0	2.3	2.2	2.0	2.0
Workplaces	0.0	0.0	2.7	6.0	2.7	1.2	1.5	3.2	4.0	4.0	4.0	4.0	4.0	4.0	2.7
Stay-at-home	0.0	0.0	2.3	4.0	3.7	1.4	1.5	1.3	1.0	1.7	4.0	4.0	4.0	4.0	4.0
Borders	0.0	0.0	3.9	6.0	6.0	5.7	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0
Total	0.0	0.0	12.8	22.0	17.8	12.2	12.0	13.5	12.3	13.1	15.0	15.3	15.2	15.0	13.7

Table A.2 (continued). Severity of COVID-19 Containment Measures: Country Indices

	01/20	02/20	03/20	04/20	05/20	06/20	07/20	08/20	09/20	10/20	11/20	12/20	01/21	02/21	03/21
United Kingdom															
Schools	0.0	0.0	2.0	6.0	6.0	3.1	3.0	2.4	2.0	2.4	2.3	2.6	5.6	5.1	2.2
Workplaces	0.0	0.0	2.2	6.0	4.0	4.0	4.0	4.0	4.0	4.0	3.9	3.6	5.6	6.0	4.4
Stay-at-home	0.0	0.0	1.2	3.9	2.9	1.5	1.0	1.0	1.2	2.0	2.0	1.7	3.7	4.0	2.7
Borders	0.0	0.0	0.0	0.0	0.0	3.1	4.0	4.0	4.0	4.0	4.0	4.3	5.0	5.0	5.0
Total	0.0	0.0	5.4	15.9	12.9	11.6	12.0	11.4	11.2	12.4	12.2	12.2	19.9	20.1	14.2
France															
Schools	0.0	0.0	4.0	6.0	4.7	3.6	2.0	2.0	2.0	2.2	4.0	4.0	3.5	2.0	2.0
Workplaces	0.0	0.0	2.9	6.0	4.3	2.0	2.0	2.0	2.0	2.4	5.7	4.0	4.0	3.9	3.1
Stay-at-home	0.1	0.1	1.9	3.9	2.7	1.4	0.1	0.1	0.1	1.3	4.0	4.0	4.0	4.0	3.5
Borders	0.5	2.0	3.4	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0
Total	0.6	2.1	12.1	20.9	16.8	12.0	9.1	9.1	9.1	10.9	18.7	17.0	16.5	14.9	13.6
Italy															
Schools	0.0	0.5	5.7	6.0	6.0	6.0	6.0	6.0	3.7	2.0	3.7	4.0	2.6	2.5	3.0
Workplaces	0.0	0.6	4.9	6.0	3.5	4.0	3.7	2.9	4.0	3.4	2.9	3.4	4.4	4.0	3.1
Stay-at-home	0.0	0.3	3.9	4.9	2.4	2.0	1.7	0.0	0.0	0.5	3.5	4.0	4.0	4.0	4.0
Borders	0.5	5.0	5.0	5.0	4.6	3.5	4.6	4.8	5.0	4.7	4.8	5.0	5.0	5.0	5.0
Total	0.5	6.4	19.6	21.9	16.5	15.5	16.0	13.7	12.7	10.6	14.9	16.4	16.0	15.5	15.1
Russia															
Schools	0.0	0.0	1.9	3.6	3.0	3.0	2.4	2.0	2.0	2.0	2.0	2.0	2.0	2.0	0.1
Workplaces	0.0	0.0	1.9	6.0	3.3	2.0	2.0	2.0	2.0	2.0	2.0	2.0	1.9	1.0	1.0
Stay-at-home	0.0	0.0	2.2	3.0	3.0	2.0	2.0	1.3	0.3	1.0	1.0	1.0	1.0	2.0	1.6
Borders	0.0	5.0	5.0	6.0	6.0	6.0	5.5	5.0	5.0	4.4	4.5	5.0	5.0	5.0	5.0
Total	0.0	5.0	11.1	18.6	15.3	13.0	11.8	10.3	9.3	9.4	9.5	10.0	9.9	10.0	7.7
China															
Schools	1.4	6.0	4.4	3.0	3.0	2.0	2.0	2.0	2.1	2.3	2.4	3.0	3.0	3.0	2.0
Workplaces	0.6	3.8	3.0	2.0	2.7	3.0	3.0	3.0	2.2	2.1	2.3	2.2	2.0	2.0	2.0
Stay-at-home	0.3	2.9	3.0	1.5	2.3	3.0	3.0	3.0	1.2	1.7	2.4	3.0	3.0	2.7	2.0
Borders	0.0	0.7	4.2	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0
Total	2.2	13.5	14.5	11.5	13.0	13.0	13.0	13.0	10.5	11.0	12.1	13.2	13.0	12.7	11.0
India															
Schools	0.0	0.0	3.8	6.0	6.0	6.0	6.0	6.0	4.7	1.5	1.7	3.0	3.0	2.8	2.0
Workplaces	0.0	0.0	2.2	5.3	2.2	1.4	1.8	4.0	3.9	2.0	2.0	2.0	2.0	2.0	2.0
Stay-at-home	0.2	1.0	2.5	6.0	2.5	2.0	2.0	2.0	2.0	2.0	2.0	2.0	2.2	3.0	3.0
Borders	0.6	2.0	4.1	6.0	5.5	5.0	6.0	6.0	6.0	5.8	5.0	5.0	5.0	5.0	5.0
Total	0.8	3.0	12.6	23.3	16.2	14.4	15.8	18.0	16.6	11.3	10.7	12.0	12.2	12.8	12.0
Japan															
Schools	0.0	0.0	2.8	3.0	3.0	2.0	2.0	2.0	2.0	2.0	2.0	2.0	2.0	2.0	2.0
Workplaces	0.0	0.4	2.0	2.0	1.1	0.0	0.0	1.0	0.3	0.0	0.8	1.0	1.0	1.0	1.2
Stay-at-home	0.0	0.0	0.0	1.3	1.1	0.0	0.3	1.0	1.7	2.0	2.0	2.0	2.0	2.0	2.0
Borders	2.2	5.0	4.2	4.9	5.0	5.0	5.0	5.0	4.2	3.9	5.0	5.3	6.0	6.0	5.8
Total	2.2	5.4	9.0	11.2	10.2	7.0	7.3	9.0	8.1	7.9	9.8	10.3	11.0	11.0	11.0

Table A.2 (continued). Severity of COVID-19 Containment Measures: Country Indices

	01/20	02/20	03/20	04/20	05/20	06/20	07/20	08/20	09/20	10/20	11/20	12/20	01/21	02/21	03/21
								Australia							
Schools	0.0	0.0	0.6	2.6	2.0	2.0	2.3	2.9	2.9	2.0	1.4	1.0	1.0	1.5	1.3
Workplaces	0.0	0.0	0.5	2.0	2.0	2.0	2.0	2.9	2.9	1.9	1.0	2.5	1.7	2.3	2.0
Stay-at-home	0.0	0.0	0.5	2.0	1.7	0.0	2.2	2.0	2.0	1.9	1.8	2.0	0.7	0.9	0.2
Borders	0.0	4.7	5.3	6.0	6.0	6.0	6.0	6.0	6.0	6.0	6.0	6.0	6.0	6.0	6.0
Total	0.0	4.7	6.9	12.6	11.7	10.0	12.4	13.8	13.7	11.8	10.2	11.5	9.4	10.6	9.5

Note: This table contains the input numbers used in Figure 6.

or at some regions, and we double the number if the implementation was nationwide. For the borders category, there are five degrees of severity and, by definition, the implementation was made nationwide or at a country level. In that case, our quantitative index goes from 0 to 6. In Table A.2 we present our quantitative index for a set of 15 countries. This data is used as input for Figure 6 in the paper.

Additional data description

Mexican Government bonds spreads

The annual yields that correspond to 2- and 10-year bonds are calculated from the end-of-week synthetic yield curve of Mexico's Treasury Certificates (i.e., Cetes), which provides yields for daily maturities. As such, we annualized the yields for nodes 728 and 3600 days to obtain the 2 and 10-year bond annual yields, respectively, as follows:

$$\left[\left(\left(\frac{Yield}{100}\right)\left(\frac{Node}{360}\right)+1\right)^{\frac{364}{Node}}-1\right]100 \, .$$

Uncertainty measures for Mexico

Uncertainty measures regarding Mexico's economic situation (*EUNC*) and Mexico's economic policy (*PUNC*) correspond to the percentage of private sector specialists who consider that uncertainty regarding the domestic economic situation, or its economic policy, represent an obstacle for economic growth. The variable related to Mexico's investment climate *ICLIM* refers to the percentage of private sector specialists who expect said variable to deteriorate in the following six months.

Country risk

Since country risk indicators partially reflect global risk, we use principal component analysis to extract the common factor driving the dynamics of the EMBI plus spreads for the regions of Latin-America, Europe, Africa, and Asia. We denominate such a factor as $EMBI^{W}$. Then, we remove the effect of this global factor on Mexico's EMBI plus spread through an OLS regression. We rename the residuals from said regression as $EMBI^{MX}$, which is a measure of idiosyncratic factors governing the country risk of Mexico.

Prior and posterior distributions

In this Section, we discuss the priors used to estimate the parameters of model (2.1)-(2.2), and the steps followed in the Gibbs sampler. In particular, we use a set of natural conjugate priors for all estimating parameters, so the conditional posterior distribution $\phi(\vartheta|Y)$, where $\vartheta = \{\{f_t\}_{t=1}^{T}, A, H, R, Q\}$ and $Y = \{Y_t\}_{t=1}^{T}$, has the same distribution family as the prior distribution $\varrho(\vartheta)$. As such, we assume that the priors for f_1, A and H are independent normal distributions with mean $f_{1|0}$, A_0 and H_0, respectively, and variance equal to $p_{1|0}$, σ_{A0}, σ_{H0}. For f_t with $t > 1$, we use the Kalman filter, which conditions the one-period-ahead forecast of the state variable on all available information in the current period, i.e. $f_{t+1|t} = \kappa(f_t, \{Y_k\}_{k=1}^{t})$. In turn, the prior distributions for Q and R are an independent inverse gamma distribution, and an independent inverse Wishart distribution, respectively, with scales Q_0 and R_0, and degrees of freedom $q = 2$ and $r = n + 1$.

We fixed the prior means and variances as follows. For the period for which all variables in Y are available, say from t_0 onward, we compute vector $\tilde{f} = \{\tilde{f}_{t0}, \tilde{f}_{t0+1}, \ldots, \tilde{f}_T\}$ using the first principal component of $\{Y_k\}_{k=t_0}^{T}$. Thus, we set Q_0 equal to $\text{var}(\Delta\tilde{f}_t) \times 1e^{-2}$. Then, H_0 is obtained as the OLS estimate of H in the auxiliary regression $Y_t = H\tilde{f}_t + e_{H,t}$, while $\sigma_{H_0} = var(e_{H,t}) \times (\tilde{f}'\tilde{f})^{-1}$. Similarly, A_0 is obtained as the OLS estimate of A in the auxiliary regression $Y_t - H_0\tilde{f}_t = AX_t + e_{A,t}$, while $\sigma_{A_0} = R_0 \times (X'X)^{-1}$ and $R_0 = \text{diag}(\text{var}(e_{H,t}))$. Finally, $f_{1|0} = 0$ and $p_{1|0} = Q_0 \times 100$. By assuming a large value for $p_{1|0}$ with respect to Q_0, the initial value for $f_{1|0}$ has minor importance for the estimated posterior sequence of f_t.

Given the prior distributions of all estimating parameters, their conditional posterior distributions are computed through MCMC iterations using the following Gibbs sampler:

1. Draw f_1 from $\phi(f_1|Y, X, H, A, R, Q) \sim \mathcal{N}(f_{1|0}, p_{1|0})$, then draw f_t for $t > 1$ from $\mathcal{N}(f_{t|t}, p_{t|t})$, where $f_{t|t}$ and $p_{t|t}$ are the mean and variance of f_t stemming from the updating equations of the Kalman filter.

2. Draw Q from $\phi(Q|Y, X, f, H, A, R) \sim i\mathcal{G}(s_Q, T + q)$.

3. Draw H from $\phi(H|Y, X, f, A, R, Q) \sim \mathcal{N}(\mu_H, \sigma_H)$.

4. Draw A from $\phi(A|Y, X, f, H, R, Q) \sim \mathcal{N}(\mu_A, \sigma_A)$.

5. Draw R from $\phi(R|Y, X, f, H, A, Q) \sim i\mathcal{W}(s_R, T + r)$.

The conditional posterior moments are given by:

$$s_Q = Q_0 + (v'v),$$
$$\sigma_H = \left(\sigma_{H_0}^{-1} + R^{-1} \otimes (f'f)\right)^{-1},$$
$$\mu_H = \sigma_H \left(\sigma_{H_0}^{-1}\text{vec}(H_0) + R^{-1} \otimes (f'f)\text{vec}(H^*)\right),$$

$$\sigma_A = \left(\sigma_{A_0}^{-1} + R^{-1} \otimes (X'X)\right)^{-1},$$
$$\mu_A = \sigma_A \times \left(\sigma_{A_0}^{-1}\mathrm{vec}(A_0) + R^{-1} \otimes (X'X)\mathrm{vec}(A^*)\right),$$
$$s_R = R_0 + (w'w),$$

where $H^* = (f'f)^{-1}\big(f'(Y - AX)\big)$, and $A^* = (X'X)^{-1}\big(X'(Y - Hf)\big)$.

Adjusting the Kalman filter for missing values

The set of financial and survey-based variables considered for the estimation of *FCI* is not entirely available until March 2002. Therefore, we need to adjust the Kalman filter for the presence of missing values in vector Y_t in certain periods. We describe this process below.

For every date t, we set a selector matrix J_t of order $m_t \times n$, where $m_t \leq n$ for every t. As stated in model (2.1)-(2.2), n is the total number of variables in vector Y_t. In turn, m_t is the number of non-missing values in vector Y_t in time t. To see how the selector matrix J_t is set, suppose $n = 5$ and in time $t = i$ the second and third rows of Y_i are missing, e.g.

$$Y_i = \begin{bmatrix} 5 \\ nan \\ nan \\ 1 \\ 8 \end{bmatrix}$$

then J_i is a 3 × 5 matrix of the form

$$J_i = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}.$$

To keep only the observed values of Y_i, pre-multiply J_i to this vector to obtain

$$Y_i^* = J_i Y_i = \begin{bmatrix} 5 \\ 1 \\ 8 \end{bmatrix}.$$

Notice that if all variables in Y_t are observed, then J_t is simply an identity matrix of order $n \times n$. As such, without loss of generality, we can transform the observation equation (2.1) to take the form

$$Y_t^* = A_t^* X_t + H_t^* f_t + w_t^*, \qquad \text{(D.1)}$$

where

$$Y_t^* = J_t Y_t$$
$$A_t^* = J_t A$$
$$H_t^* = J_t H$$
$$w_i^* = J_t w_t$$

According to the adjusted observation equation, the variance of w_t^* equals $R_t = J_t R J_t'$. Equations (D.1) and (2.2) can be then put into the Kalman filter to obtain estimates of the latent factor f_t for the complete sample period.

Alternative FCIs

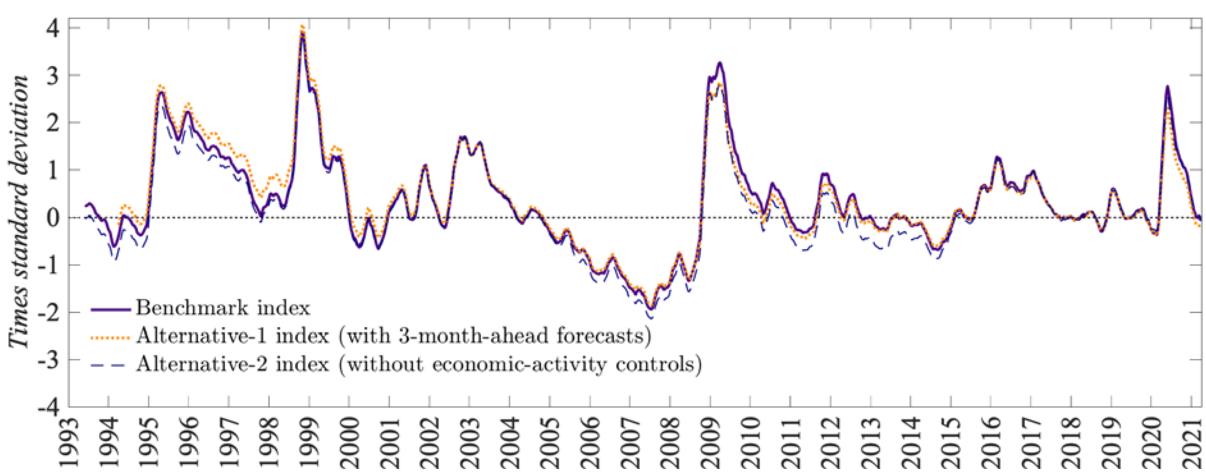
In equation (2.1), similar to Hatzius *et al.* (2010) and Koop and Korobilis (2014), we include current indicators of Mexico's IGAE and the U.S.' Industrial Production Index (IPI) to ensure that *FCI* reflects only financial conditions. However, since asset prices react immediately to news, it is possible that *FCI* also reflects expectations about future economic activity. In this Section, we propose two alternative specifications of equation (2.1) to indirectly assess the impact of economic activity on the *FCI*. These alternatives are:

$$Y_t = AX^e_{t+12} + Hf^{a,1}_t + w_t \tag{E.1}$$

$$Y_t = Hf^{a,2}_t + w_t \tag{E.2}$$

In the first alternative, we replace current economic activity indicators by their 12-week-ahead, or 3-month-ahead, forecasts. In the second alternative, we remove completely real-activity variables from the measurement equation. It is worth noticing that IGAE forecasts from professional forecasters are not available until late in the sample, in the year 2000. For this reason, we build X^e_{t+12} as the 3-step-ahead forecast from a monthly BVAR model involving solely the IGAE and IPI indicators, where we assume that the latter is block-exogenous to the former.

Figure E.1. Alternative financial conditions indexes



Given these two alternatives, we re-estimate the dynamic factor model presented in Section 2.1 following the same steps described in Section C and Section 3 in the paper. The results are shown in Figure E.1. Remarkably, the two alternative indices remain very close to the benchmark *FCI*. The greatest differences appear between the benchmark and alternative 2, that is, when no economic activity variables are considered in the estimation. This suggests that current economic activity is indeed shaping some of the dynamics of the asset prices contained in the *FCI*, although the extent of this effect seems somehow limited.