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Economic Growth at Risk: An Application to Chile*

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Abstract

This paper applies the Growth-at-Risk (G@R) methodology proposed by Adrian et al. (2019) to the Chilean economy. To this aim, we first develop a Financial Conditions Index (FCI) from a broad set of local and external macro-financial variables covering the period from 1994 to 2020, such as asset prices, short and long-term spreads, and volatility measures that characterizes the vulnerabilities of the domestic financial market. The FCI identifies periods of substantial tight financial conditions that coincide with several episodes of economic downturns and market turmoils such as the 1997 Asian Crisis, the 2007-2009 Global Financial Crisis, and the coronavirus pandemic in mid-March 2020. The G@R analysis reveals that the FCI contains relevant information to forecast lower future GDP growth distribution quantiles. Thus, our results show that downside risks to growth intensify during periods of economic and financial distress. In particular, the 5th percent quantile of economic growth during the 2007-2009 Global Financial crisis reached roughly -10% due to tighter financial conditions propelled by the deterioration of the credit to GDP gap and adverse external conditions such as higher global volatility and lower terms of trade. These findings, and others discussed in the paper, highlight this methodology's usefulness as an additional tool to support monitoring and risk management duties by policymakers.

Resumen

Este artículo utiliza la metodología crecimiento en riesgo (G@R, por sus siglas en inglés Growth-at-Risk) propuesta por Adrian et al. (2019) para el caso de la economía chilena. Con este objetivo, primero desarrollamos un Índice de Condiciones Financieras (ICF) utilizando un conjunto amplio de variables macro-financieras locales y externas del período entre 1994 a 2020, como precios de activos, spreads de corto y largo plazo, y medidas de volatilidad, las que darían cuenta de las vulnerabilidades del mercado financiero doméstico. El ICF identifica períodos de condiciones financieras sustancialmente ajustadas, las cuales coinciden con varios episodios de recesiones económicas y turbulencias en los mercados como la Crisis Asiática de 1997, la Crisis Financiera Global de 2007-2009, y la pandemia del coronavirus a mediados de Marzo de 2020. El análisis G@R revela que el ICF contiene información relevante para pronosticar los cuantiles inferiores de la distribución de crecimiento futuro del PIB. De este modo, nuestros resultados muestran que los riesgos a la baja para el crecimiento se intensifican durante períodos de dificultades económicas y financieras. En particular, el quinto cuantil del crecimiento económico durante la Crisis Financiera Global de 2007-2009 alcanzó cerca de -10% debido a las condiciones financieras más ajustadas como consecuencia del deterioro en la brecha crédito a PIB y condiciones externas adversas caracterizadas por mayor volatilidad y términos de intercambio menores. Éstos hallazgos, junto con otros discutidos en el artículo, destacan la utilidad de esta metodología como una herramienta adicional para apoyar tareas de monitoreo y gestión de riesgos por parte de los formuladores de políticas.

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1 Introduction

In recent years, policymakers and macroprudential supervisors of a growing number of countries worldwide have increased their efforts in identifying downside risks and systemic vulnerabilities of financial markets to quantify their effects on the overall economy. In this context, the related literature has developed vastly. Some of the topics covered are the prediction of systemic risk events (LoDuca and Peltonen, 2011; Arsov *et al.*, 2013; Blancher *et al.*, 2013), uncertainty measurement and its role for downside risks (Jurado *et al.*, 2015; Baker *et al.*, 2016; Carriero *et al.*, 2018), the link between financial development and economic growth during periods of financial instability (Lown *et al.*, 2000; Hakkio and Keeton, 2009; Bauducco *et al.*, 2011; Carlson *et al.*, 2011), and the design of policy instruments mitigating the buildup of financial instability (Lim *et al.*, 2011; CGFS, 2012), among others.

One related methodology that has become quite popular since its first use in the Global Financial Stability Report of October 2017 (IMF, 2017) is the *Growth-at-Risk* (*G@R*) framework developed by Adrian *et al.* (2019). In short, the *G@R* analysis is a prospective tool to quantify risks that uses quantile regressions to relate current macro-financial conditions, characterized by actual GDP growth and a Financial Conditions Index (FCI), to the distribution of future economic growth. This framework's main advantage is its ability to assess the entire distribution of future GDP growth instead of point forecasts and quantify the likelihood of risk scenarios that would serve as an additional early-warning indicator for policymakers. Therefore, *G@R* should not be considered as a forecasting tool.

In this paper, we conduct the *G@R* analysis for the Chilean economy following a modified version of the guidance offered in Prasad *et al.* (2019), which we detail below. First, we construct an FCI for Chile using 11 variables over the period from 1994 to 2020, both local and external, including asset prices, spreads, and volatility measures and variables like industrial production and terms of trade. Then, we aggregate them using weights computed by Principal Components. Second, we forecast the one-year-ahead conditional distribution of GDP growth using a general FCI instead of partitions of financial conditions. This formulation allows us to characterize Chilean financial markets' current stance and their impact on growth with one metric. In contrast, the effects of an individual partition (e.g., price of risks, cost of funding, access to financing, and degree of financial stress, among others) can be assessed by looking at their corresponding weights within the FCI. Finally, we derive the conditional future growth distribution from a smoothed version of the quantile regression predictions by fitting a parametric distribution with skewness to predicted values. To address downside risks to growth, we focus our attention on the evolution over time of the 5th percent quantile of this distribution and, alternatively, the probability of a GDP contraction.

Our results reveal that the FCI displays episodes of significant tighter financial conditions that coincide with several periods of economic crisis and financial distress in Chile, like the Asian Crisis of 1998-1999, the Global Financial Crisis of 2007-2009, the civil protests and riots in mid-October 2019, and the COVID-19 pandemic in mid-March 2020. Moreover, the *G@R* analysis reveals that the FCI contains relevant information to forecast lower quantiles of GDP growth's conditional distribution. Hence, the one-year-ahead forecasts for the 5th percentile of this variable depict major reversals during tight financial conditions or, in another way, the likelihood of an adverse growth scenario spikes sharply. For instance, in the course of the 2007-2009 Global Financial crisis, the conditions in Chilean financial markets tightened

considerably during the last quarter of 2008 due to the deterioration of the VIX, terms of trade, and the credit to GDP gap, mainly. Consequently, downside risks to growth deepened such that the 5th percentile of growth reached values close to -10% during this period or, looking at an alternative metric, the probability of a GDP decline jumped to about 40%.

The document is organized as follows. Section 2 provides a general review of the elements required for implementing the G@R methodology and describes the procedure employed to compute the Chilean economy’s FCI. Section 3 presents the evolution of the FCI and G@R during the last two decades and discusses their main features and predictions. Finally, Section 4 concludes. We leave all technical details in the Appendix of the document.

2 Methodology

In this section, we broadly describe the Growth-at-Risk methodology and its components, and we briefly revise some international applications and extensions of this tool. Lastly, we outline how we compute the Financial Conditions Index —an essential input for the G@R analysis— that characterizes the Chilean financial market and its vulnerabilities.

2.1 Growth at Risk

As mentioned in the Introduction, the Growth-at-Risk (G@R) methodology proposed by [Adrian *et al.* \(2019\)](#) is an econometric tool that allows the estimation of the full distribution of future real GDP growth conditional on the current economic and financial conditions using quantile regressions (see [Koenker and Bassett, 1978](#)). In this sense, G@R is a prospective policy tool intended to quantify risks to economic growth¹.

To formalize the previous idea, let y_{t+h} be the h -quarters ahead annual real GDP growth and fci_t be an index that characterizes the overall economy’s current financial conditions. Further, let τ be a scalar in the $(0, 1)$ interval, and $g(\cdot|y_t, fci_t)$, and $G(\cdot|y_t, fci_t)$ be the probability density function and the cumulative distribution function of y_{t+h} conditional on y_t and fci_t , respectively. With these definitions at hand, the τ th conditional quantile function of the h -quarters ahead real GDP growth, given the current macro-financial conditions of the economy, $\mathcal{Q}_{y_{t+h}}(\tau|y_t, fci_t) \equiv \inf\{y_{t+h} : G(y_{t+h}|y_t, fci_t) \geq \tau\}$, is given by

$$\mathcal{Q}_{y_{t+h}}(\tau|y_t, fci_t) = \alpha(\tau) + \beta(\tau)y_t + \gamma(\tau)fci_t \tag{1}$$

for all $\tau \in (0, 1)$ and $h = 0, 1, 2, \dots$. Note that, unlike OLS regressions, the coefficients $\theta(\tau) = [\alpha(\tau), \beta(\tau), \gamma(\tau)]'$ in expression (1) are quantile-specific. This feature allows for a differentiated forecasting power of both y_t and fci_t on the h -quarters ahead GDP growth. [Adrian *et al.* \(2019\)](#) argue that one key property of G@R is the larger impact, in absolute value, of current financial conditions on economic growth forecasts ($\gamma(\tau)$) when the economic scenario is adverse, i.e., when τ is small. Hence, $g(\cdot|y_t, fci_t)$ is not necessarily symmetric.

¹It is worth noticing that G@R is different from the GDP growth fan charts published in the Monetary Policy Report of the Central Bank of Chile. Fan charts are graphical tools that report a set of confidence bands for economic growth forecasts, i.e., for GDP growth’s conditional expected value. Quantile regressions, in contrast, consists of point estimates of any part (or quantile) of the conditional distribution of future GDP growth, not only of its central part.

An asymptotic characteristic of quantile regressions is that it allows us to look at slices of the conditional distribution of y_{t+h} , $h = 0, 1, 2, \dots$, without any global distributional assumption. In other words, we use only local information around the quantile of interest $\tau \in (0, 1)$ to compute the estimators $\theta(\tau)$. This characteristic implies that $\mathcal{Q}_{y_{t+h}}(\tau|y_t, fci_t)$ is a monotonic, non-decreasing function of τ . However, in small samples, the monotonicity of the conditional quantile function is not guaranteed. This observation is an issue known as *quantile crossing* that redounds in negative values of the probability density function $g(\cdot|y_t, fci_t)$, thus violating one axiom of probability functions.

Although there are several methodologies to fix the quantile crossing problem², the conditional distributions obtained via quantile regressions are not smooth in general. In this sense, to achieve smoothness, [Adrian et al. \(2019\)](#) fit a skewed t -distribution developed by [Azzalini and Capitanio \(2003\)](#), whose inverse cumulative distribution function or τ th quantile function is given by the following expression

$$F^{-1}(\tau; \mu, \sigma, \nu, \xi) = \begin{cases} \frac{t^{-1}(\tau(1+\xi^2)/2, \nu) - \mu\xi}{\sigma\xi} & \text{if } \tau < \frac{1}{1+\xi^2} \\ -\frac{\xi t^{-1}((1-\tau)(1+\xi^{-2})/2, \nu) + \mu}{\sigma} & \text{if } \tau \geq \frac{1}{1+\xi^2} \end{cases} \quad (2)$$

where the four parameters pin down the location μ , scale σ , fatness ν , and shape ξ of the previous function, and $t^{-1}(\cdot, \nu)$ is the inverse cumulative distribution function of a standardized t -distribution with ν degrees of freedom.

Then, for each quarter t and forecasting horizon h , the authors choose these four parameters to minimize the squared distance between the estimated τ th conditional quantile function $\hat{\mathcal{Q}}_{y_{t+h}}(\tau|y_t, fci_t)$ and the corresponding quantile function of the skewed t -distribution (2) to match the 5, 25, 75 and 95 percent quantiles.

Finally, the fitted skewed t -distributions are used to measure the vulnerability of the predicted path of GDP growth to unexpected shocks. In particular, the authors consider metrics of entropy of the fitted conditional probability density function relative to the unconditional one and the expected shortfall and expected longrise to assess downside and upside risks to the GDP growth forecasts.

2.1.1 International Experience

The G@R methodology —and some extensions of this tool— has been used by several countries to quantify macro-financial risks and identify the overall economy’s principal vulnerabilities. In this section, we revise some international experiences in this regard.

In Canada, the Bank of Canada (BoC) applied G@R on future GDP growth, conditional on household indebtedness ([BoC, 2018](#)). In their Financial System Review report, BoC shows that G@R worsened in 2015, mostly because of an oil price shock’s macroeconomic implications. However, since 2016, the growth of household indebtedness and housing market imbalances has weighed on G@R, even though macroeconomic performance improved. In an interesting approach, the BoC uses G@R as a tool for monitoring the household sector’s effect on future GDP. In particular, they follow the 5th percentile of the one-year-ahead forecast of

²See [Mammen \(1991\)](#), [He \(1997\)](#), [Koenker and Ng \(2005\)](#), [Dette and Volgushev \(2008\)](#), and [Chernozhukov et al. \(2010\)](#), among others.

GDP growth with and without the vulnerabilities characterized by household indebtedness to support policy decisions. For example, they discuss how policy actions designed to slow down the accumulation of household debt and house price growth could reduce GDP growth in the medium run, but, at the same time, could also reduce the chances of a severe GDP contraction, as measured by G@R.

In a country report, IMF (2018b) implements G@R for Portugal, considering three conditioning variables: the price of risk, credit aggregates such as leverage and credit growth, and external conditions. These variables, constructed using Principal Component Analysis (PCA) on a broader set of variables, summarize the Portuguese economy's relevant macro-financial conditions. The data covers the period between 1999 to 2018 on a quarterly frequency. The results from quantile regressions support the hypothesis of a non-linear relationship between financial conditions and future GDP growth. However, the informational content of each variable depends on the forecasting horizon. For instance, the price of risk is a relevant conditioning variable to forecast downside risks to GDP growth at horizons of one to eight quarters, but it is uninformative over longer horizons. On its part, credit aggregates identify downside risks to GDP growth at horizons of four to 12 quarters ahead, whereas external conditions signal tighter external conditions within a three-year horizon. The report uses G@R to estimate the tail risks around the baseline scenario for GDP growth. Based on the financial conditions in the first quarter of 2018, in a severely adverse scenario (5th percentile), GDP would fall below 1.3 percent one-year ahead and below 0.9 percent within two-to-three-years ahead.

Further, in the context of the 2018 Article IV consultation with Albania, IMF (2019a) considers the G@R approach with five PCA-based conditioning variables: (i) current GDP growth, (ii) domestic financial conditions, (iii) domestic leverage, (iv) trade partners macroeconomic conditions, (v) financial conditions in the euro area, and (vi) world financial conditions. Data coverage starts in 2003, at a quarterly frequency, and ends in 2018. The results show that trading partners' macroeconomic conditions significantly impact Albania's growth forecasts, both on average and in bad times. However, the median and the 10th percentile coefficient are statistically similar, implying a linear effect of this conditioning variable on the GDP growth distribution's left tail. Leverage has the second-highest effect, which amplifies a shock to growth in bad times. The consultation considers a scenario of an adverse shock to the two previous variables, concluding that, if this scenario materializes, it would cost Albania, on average, 1.8 to 2 percentage points of GDP growth within one year.

In Panama, the G@R methodology applied in IMF (2019b) estimates the conditional density forecast of future GDP growth using quantile regressions with the following regressors: the price of risk, leverage, external financial conditions, and external demand. Data covers the period between 2004 and 2018 at a quarterly frequency. External financial conditions are the primary driver of Panama's short-term growth prospects. In contrast, the build-up of financial vulnerabilities related to leverage is the crucial link between financial conditions and Panama's medium-term growth outlook. Leverage has a smaller effect on growth at short horizons but a negative effect—that dominates the price of risk and external conditions—at longer horizons. The report uses the G@R framework to forecast GDP growth under severely adverse scenarios for one, two, and three years ahead, conditional on current financial conditions. The resulting conditional distributions were also used to assess the cumulative likelihood of growth scenarios used by Panama's Superintendency of Banks in its stress-test

scenarios.

Lastly, in Peru, IMF (2018a) identifies three statistically significant risk factors on future GDP growth: external conditions, leverage, and price of risk. External conditions, which are mostly driven by China’s economic growth and foreign exchange developments in Peru, were identified as the crucial factor that can lead to tail outcomes for GDP growth. The contribution of these two variables to tail risks is twice as high as the contribution of leverage and the price of risk. Like the case of Panama, in Peru, G@R was used as an input to the stress tests conducted by the Superintendence of Banks to characterize the cumulative likelihood of the Peruvian GDP growth path under an adverse scenario.

Some extensions of the G@R methodology consider real estate prices, capital flows, and inflation. In the first case, IMF (2019c) forecasts the distribution of future real house price growth conditional on financial conditions, real GDP growth, overvaluation characterized by the ratio of house prices to GDP per capita, and credit booms. This exercise is intended to assess and quantify the downside risks to the real estate market in a sample of 32 advanced economies, in the context of its Global Financial Stability Report. In the second case, Gelos *et al.* (2019) predict the entire future probability distribution of capital flows to emerging markets, based on current domestic structural characteristics, policies, and global financial conditions, to quantify capital flows risks and evaluate policy tools to mitigate them. In the last case, Banerjee *et al.* (2020) compute the four-quarters-ahead distribution of inflation, conditional on its traditional drivers such as economic activity, oil price, financial conditions, and exchange rate, for a set of advanced and emerging economies. They find that inflation risks —downside, upside, or both— have increased almost everywhere recently.

2.2 Financial Conditions Index

As mentioned in the previous section, the G@R methodology is based on quantile regressions, where the conditioning or independent variables are the current GDP growth, y_t , and an index that characterizes the overall economy’s current financial conditions, fci_t . Hence, in this section, we describe in detail how we construct a Financial Conditions Index (FCI) for Chile.

The importance of considering a measure of financial conditions within the G@R framework finds in the role that financial markets play in transmitting the monetary policy to the economy’s real side through two main channels. The first one is related to how changes in the short-term rates —related to the policy rate— affect agents’ expectations that modify long-term rates and their investment and consumption decisions. The second channel arises from the credit channel’s imperfections, which can affect institutional investors, financial entities, and banks. Hence, one of the motivations of an FCI is to collect these phenomena and quantify possible imbalances’ effects. This type of tool’s availability becomes of particular relevance in the context of monitoring risks that may affect the economy’s financial stability.

We closely follow the methodology proposed by both the IMF and other entities. The informational content of a broad set of variables that characterizes the local financial market —such as asset prices, short and long-term spreads, volatility indicators, among other variables— is reduced or aggregated using PCA. Thus, the FCI is just one or several factors computed under this methodology, which summarizes the joint dynamics of the observable financial variables, and can be understood as an indicator of how tight are the overall financial

market conditions.

Table 1 shows 11 macro-financial variables, both local and external, that we consider in constructing the FCI for Chile. The selection of variables aims to characterize, in a broad sense, the main features of the local financial market and is in line with various estimates of FCIs by the IMF. Further, we also consider statistical aspects to choose the variables. First, all variables in our sample should have a correlation coefficient with the remaining variables in the dataset less or equal than 0.8 in absolute value to avoid duplicating informational content. Second, we privilege variables with a long time record, commonly used in market monitoring duties and readily available³. Accordingly, the local macro-financial variables that we consider are the real yield of the 10-years sovereign bond (r_t^s), the spread between the interest rate on deposits and the 3-months sovereign rate (s_t^s), the real interest rate spread between corporate and sovereign bonds with maturities of around five years (s_t^c), the country risk premium proxied by the EMBI Chile ($embi_t$), the price-to-earnings ratio of the local stock market (PE_t), the volatility of stock returns (σ_t), the credit-to-GDP gap (CY_t), and the annual change of the Industrial Production Index ($ipit_t$). Regarding the external variables, we consider the yearly change of the terms of trade (tot_t), the real exchange rate (e_t), and the CBOE implied volatility index (vix_t). These variables span the period between March 1994 to June 2020⁴. Thus, our dataset contains several economic crises and episodes of financial market stress, such as the 1997 Asian Crisis, the 2007-2009 Global Financial Crisis, the civil protests and riots in Chile in mid-October 2019, and the ongoing market turmoil triggered by the COVID-19 pandemic, officially declared in mid-March 2020.

As mentioned previously, we aggregate the macro-financial variables by using PCA. To understand how this methodology works in detail, let $X_t = [r_t^s, s_t^s, s_t^c, embi_t, PE_t, \sigma_t, CY_t, ipit_t, tot_t, e_t, vix_t]'$ be a vector that collects observations of these variables at time t . The PCA methodology within the FCI context considers the standardized version of all macro-financial variables (\tilde{X}_t) and decomposes its joint dynamics in the following manner

$$\tilde{X}_t = \Lambda f_t + u_t \quad (3)$$

where f_t is a scalar, typically known as the common factor of X_t , Λ is a vector of coefficients that contain each macro-financial variable's sensitivities to the common factor, and u_t is an error term satisfying $E[u_t] = 0$ and $E[u_t u_t'] = \Sigma_u$. Because all elements on the right-hand side of equation (3) are unobserved, the methodology imposes the restriction $T^{-1} \sum_{t=1}^T f_t^2 = 1$ to identify both the common factors and the sensitivities of the model, where T is the sample size. Note that because f_t only varies across time, it summarizes the joint dynamics of the macro-financial variables in \tilde{X}_t over time. Hence, the common factor of model (3) corresponds to the FCI.

There are several ways to estimate the previous model. The most popular one is the eigendecomposition of the data matrix $\tilde{X} = [\tilde{X}_1, \tilde{X}_2, \dots, \tilde{X}_T]'$. In this setup, the vector

³This last point is relevant, especially in emerging economies, where data is not always available, is recorded at lower frequencies, or the span is relatively short.

⁴The only exception is EMBI Chile, which is available from June 1999 onwards. We extended these time series backward until January 1994 by running an OLS regression of EMBI Chile against the EMBI of China, Mexico, and the Philippines, using data from 1994 to 2020. Then, the imputed values to the missing observations of EMBI Chile correspond to this regression's fitted values (R^2 coefficient is around 62%). The results are robust to different sample sizes.

of estimated common factors or Financial Conditions Index $\widehat{FCI} = [\widehat{fci}_1, \widehat{fci}_2, \dots, \widehat{fci}_T]'$ is equal to \sqrt{T} times the eigenvector of the matrix $\tilde{X}\tilde{X}'$, and the vector of estimated sensitivities $\hat{\Lambda}$ is related to the eigenvalues of the previous matrix. In the Appendix, we show that the FCI can be alternatively computed as

$$\widehat{FCI} = \frac{\tilde{X}\hat{\Lambda}}{\sigma(\tilde{X}\hat{\Lambda})} \quad (4)$$

where $\tilde{X}\hat{\Lambda}$ is a weighted average of the standardized macro-financial variables, and $\sigma(\tilde{X}\hat{\Lambda})$ is its standard deviation. In other words, the previous equation indicates that the FCI, which is the common factor of model (3), is just a standardized linear combination of the macro-financial variables that characterize the local financial market. This expression is convenient in at least three dimensions. First, it informs about the sign and magnitude of a given macro-financial variable on the FCI, which helps interpret the G@R methodology's conditional forecasts. Second, the expression allows for the aggregation of user-specified subgroups of macro-financial variables. For instance, one could aggregate local and external variables separately in the first stage to compute a local and external FCI and aggregate these two indices to get the overall FCI finally. Third, the knowledge of the matrix of sensitivities $\hat{\Lambda}$ allows for a risk scenario analysis within the G@R context. In particular, one can consider hypothetical extreme shocks to some key macro-financial variables and compute the combined effects on the FCI and the conditional distribution of future GDP growth.

3 Results

In this section, we present our main results. We start by showing the Financial Conditions Index for the Chilean economy, computed under the previously described methodology. Lastly, we report the main results of the G@R exercise. In particular, we present the distribution of future GDP growth over time, focusing on the 5th percent quantile dynamics and, alternatively, the probability of a negative economic growth one year ahead.

3.1 FCI for Chile

As mentioned in the previous section, we compute the FCI for Chile by aggregating 11 macro-financial variables covering March 1994 to June 2020, according to equation (4). To that aim, we proceed in three steps. In the first one, we standardize all variables considering their mean and standard deviation within the period from March 1994 to December 2005 (base period). This way of proceeding allows us to use the same mean and standard deviation for each macro-financial variable every time a new observation becomes available. In the second step, we compute the sensitivities $\hat{\Lambda}$ considering data up to December 2005 using PCA. Finally, in the third step, we calculate the weighted average of macro-financial variables $\tilde{X}\hat{\Lambda}$ over the entire sample. However, to be consistent with the procedure in the first step, the standardization of this average considers its standard deviation over the base period.

Nevertheless, we consider two alternative aggregations as a robustness check: real-time standardization and real-time, equal weights standardization. In the first alternative, every

time a new observation beyond the base period is released, we standardize all macro-financial variables considering their mean and standard deviation up to this time. The vector of weights $\hat{\Lambda}$, and the standardized weighted average of variables, are also computed using all information up to this time. Thus, the historical FCI time series is updated with the latest observation obtained through this real-time procedure. In the second alternative procedure, we go on similarly, but considering equal weights, i.e., $|\lambda_i| = 1$ for all macro-financial variables.

Table 2 shows the estimated sensitivities under the default aggregation procedure. We note that bond yields, spreads, volatilities, and the credit to GDP gap positively impact the FCI, whereas stock prices, industrial production, terms of trade, and the real exchange rate negatively effect this variable. Hence, this result indicates that positive (negative) values of the FCI are associated with tighter (looser) financial conditions. Among all macro-financial variables, the credit to GDP gap, VIX, stock prices, and terms of trade have the most significant effects, in absolute value, on the FCI. For instance, a one-standard-deviation increase of CY_t and vix_t would deteriorate the overall financial conditions in 0.85 and 0.77 standard deviations, respectively. Analogously, if PE_t and tot_t decrease by one standard deviation, then the FCI would increase roughly 0.64 standard deviations. Note also that all estimated sensitivities are statistically relevant at conventional significance levels.

Figure 1, on its part, shows the estimated FCI under the three alternative aggregation procedures since 1994, whereas Table 3 reports their descriptive statistics. Several aspects are worth highlighting from them. First, despite some local differences, the three alternative measures depict remarkably similar dynamics within the sample. The average pairwise correlation between them is around 0.97, and, in most cases, they tend to identify the same periods where financial conditions are looser and tighter. Second, the FCI sharp increments coincide with economic crises or periods of substantial stress in the local financial markets. In particular, the measure spikes to around four standard deviations during the 1997 Asian crisis and the 2007-2009 Global Financial Crisis. Analogously, all FCI measures climbed to roughly three standard deviations after the COVID-19 was officially declared a pandemic in mid-March 2020. Third, the events that occurred after the social protests and riots in mid-October 2019 worsened the local financial conditions⁵, although the latter remained loose. Fourth, the FCI's dynamic behavior within our sample reveals interesting patterns. In this sense, all measures are positively skewed, and their distributions have fat tails, suggesting that, although financial conditions in Chile during the last 15 years have been mostly loose to some extent, crisis periods represent extremely tight financial conditions. Moreover, the FCI depicts a high persistence, implying that the half-life of a shock to this variable lies between nine months to one year. However, during crisis periods, the half-life decreases significantly to around three months.

Figure 2 reports the contribution of each macro-financial variable to the FCI computed under the standard aggregation procedure. From this figure, we note the differential effect of each variable in each episode of distress. For example, during the 1997 Asian crisis, the spike seen in the FCI was mainly driven by the worsening of the 10-years sovereign inflation-indexed bond (BCU), corporate spreads, and the credit to GDP gap. In contrast, the rise in VIX and credit to GDP gap, together with the decline of the terms of trade, are behind

⁵Our analysis considers that most stresses in local financial markets due to the social protests occurred during the last quarter of 2019.

the tighter financial conditions during the 2007-2009 Global Financial Crisis. Meanwhile, the sharp hike of VIX during the COVID-19 outbreak pushed the FCI to levels around two standard deviations. Further, after the social protests and riots in mid-October 2019, the real exchange rate and the overall volatility deteriorated substantially. However, overall financial conditions remained loose because of the previous favorable economic environment propitiated, mainly, by low sovereign real interest rates.

3.2 G@R for Chile

We estimate model (1) using annual GDP growth and FCI, both in quarterly frequency and covering the period from the second quarter of 1994 to the last quarter of 2019. In particular, we focus our attention on the one-year-ahead ($h = 4$) forecast of the Chilean GDP growth distribution.

Figure 3 shows the estimated effect of FCI on the one-year-ahead growth forecast, $\gamma(\tau)$, for percent quantiles ranging from 1% to 99% using the full sample, as well as their corresponding confidence intervals. First, we note that the point estimate for this coefficient has a negative sign for all values of τ , i.e., tighter (looser) financial conditions today forecast a lower (higher) GDP growth within one year, independent of the future stance of the economy. Nevertheless, these effects are only significant at lower quantiles of the future growth distribution. For instance, all other things equal, a one-standard-deviation increase in FCI would imply an economic growth around two percentage points smaller, on average, within one year, under a future adverse scenario (percent quantiles below 10%). This finding is relevant because it suggests that the FCI is a significant variable to predict downside risks to GDP growth, a highly desirable property of the G@R framework, as remarked by [Adrian *et al.* \(2019\)](#).

Figure 4 exhibits the distribution of future GDP growth over time, conditional on current economic growth and financial conditions. We construct this surface following the methodology described in [Prasad *et al.* \(2019\)](#), in the sense that, for each period, we smooth the predicted quantiles of model (1) by fitting a skewed t -distribution. The results show that the entire distribution has substantial time-variation. In particular, we observe that during recession periods, the density function is negatively-skewed. On the contrary, during regular or expansion periods, the distribution is somewhat symmetric—consistent with the findings shown in the previous figure—and concentrates most of its probability mass around 4.2%, which is slightly above the average annual GDP growth over the entire sample (4.1%). Furthermore, our results show that the median and lower quantiles of future GDP growth distribution vary significantly over time, whereas the upper quantiles are comparatively more stable. This result is similar to the one reported by [Adrian *et al.* \(2019\)](#) for the US economy and suggests that downside risk to growth fluctuates much more strongly than upside risk.

Therefore, we focus our attention on the evolution of the 5th percent quantile of future growth distribution predicted by model (1) because of the previous result. To get a sense of this quantile magnitude, it corresponds to a GDP contraction of about 1.3%, unconditionally. Figure 5a exhibits the evolution of this statistic over time. We note that the 5th percent quantile shows significant declines in the course of downturn periods. For instance, during the 2007-2009 Global Financial Crisis, this measure decreased from 1% to roughly -10% by the end of this crisis due mainly to the sharp tightening of financial conditions during this period (see Figure 1). During the social protests and riots in the last quarter of 2019, the 5th

percent quantile of annual GDP growth continued its declining trend since the beginning of 2019 and turned negative (-0.2%) for the first time in six quarters propelled, mainly, by the depreciation of the real exchange rate and the substantial increase of volatility, especially in the stock market. This result suggests that downside risks to economic growth intensified gradually and moderately within 2019.

Lastly, Figure 5b shows the probability of negative economic growth, one year ahead, computed from the predicted quantiles of model (1), as an alternative way to account for downside risks to growth. We note that the ex-ante probability of a negative GDP expansion steadily increases during periods of economic and financial distress. In particular, the predicted probability of an economic contraction in the middle of the 2007-2009 Global Financial crisis was around 15%, and it climbed to almost 40% as financial conditions deteriorated. More recently, downside risks to GDP growth in the last quarter of 2019 almost doubled, compared to the previous quarter, but remained bounded. In particular, the one-year-ahead likelihood of negative economic growth by the end of 2019 was roughly 7.5%, a magnitude similar to the one seen during the Chinese stock market turbulence in 2016, albeit small compared to the 2007-2009 Global Financial Crisis. It is also interesting to note that after the European crisis and before the civil protests and riots in mid-October 2019, the one-year-ahead probability forecast of an economic contraction was nonzero and around 7%, on average.

4 Conclusions

In this paper, we apply the Growth-at-Risk methodology proposed by [Adrian *et al.* \(2019\)](#) to the Chilean economy from 1994.

To reach this objective, we first develop a Financial Conditions Index from a broad set of local and external macro-financial variables such as asset prices, short and long-term spreads, and volatility measures that characterize the domestic financial market and its vulnerabilities. This index, computed on a monthly frequency, signals periods of substantial tight financial conditions that coincide with several crisis periods and episodes of market turmoils such as the 1997 Asian crisis, the 2007-2009 Global Financial crisis, and the worldwide coronavirus outbreak in mid-March 2020. Then, we compute the distribution of the one-year-ahead GDP growth over time. Our results show substantial time-variation of this function, especially at the median and lower quantiles, which suggest sharp fluctuations of downside risk to economic growth. Hence, we record the evolution during the last 15 years of the 5th percent quantile and, alternatively, the probability of an economic contraction. Both statistics depict significant deterioration during economic and financial distress episodes, exceptionally during the 2007-2009 Global Financial crisis.

Our analysis and findings highlight this methodology's usefulness as an additional tool to support monitoring and risk management duties. On one side, the proposed FCI allows identifying and quantifying risks to financial stability and factors that can mitigate these risks. On the other hand, the measures within the G@R methodology evaluate the interaction between current macroeconomic and financial conditions and supports the assessment of the performance of the economy under a future adverse scenario, which could be a relevant additional input for policymakers.

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A Appendix

A.1 Computation of Financial Conditions Index

Start by considering model (3) in matrix notation as follows

$$\tilde{X} = \widehat{FCI} \cdot \hat{\Lambda}' + \hat{U} \quad (\text{A.1})$$

where \tilde{X} is a $T \times N$ matrix containing the standardized macro-financial variables described in Section 2.2 (thus, $N = 11$), \widehat{FCI} is a $T \times 1$ vector consisting of the estimator of the Financial Conditions Index for the Chilean economy along T periods, $\hat{\Lambda}$ is an $N \times 1$ vector containing the estimated sensitivities of each macro-financial variable to the FCI, and \hat{U} is a $T \times N$ matrix of residuals.

After post-multiplying expression (A.1) by $\hat{\Lambda}$, we have that

$$\begin{aligned} \tilde{X}\hat{\Lambda} &= \widehat{FCI} \cdot \hat{\Lambda}'\hat{\Lambda} \\ \widehat{FCI} &= \frac{\tilde{X}\hat{\Lambda}}{\hat{\Lambda}'\hat{\Lambda}} \end{aligned} \quad (\text{A.2})$$

where in the first equality, we used the fact that $\hat{U}\hat{\Lambda} = \mathbf{0}$ by definition. Let ν_T be a $T \times 1$ vector of ones. Note that the sample average of $\tilde{X}\hat{\Lambda}$ is equal to

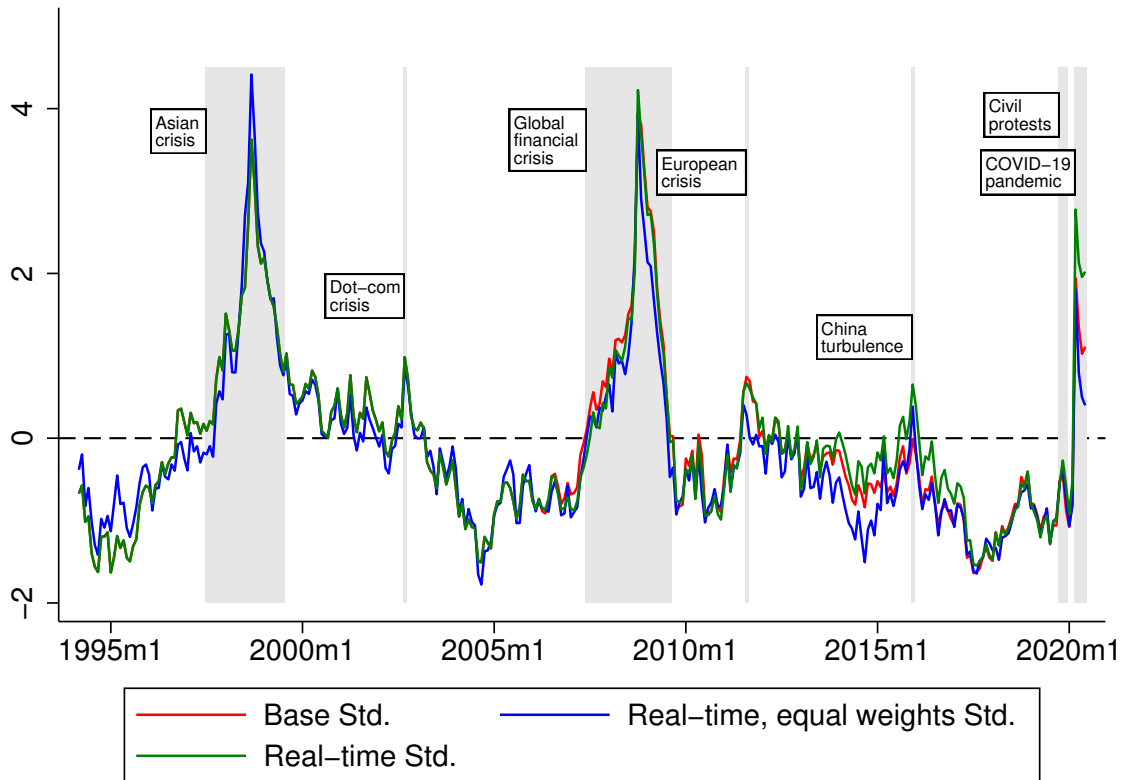
$$\frac{(\tilde{X}\hat{\Lambda})' \nu_T}{T} = \frac{1}{T} \sum_{i=1}^N \sum_{t=1}^T \hat{\lambda}_i \tilde{x}_{it} = 0$$

because the macro-financial variables are standardized. Hence, the standard deviation of $\tilde{X}\hat{\Lambda}$ is given by

$$\begin{aligned} \sigma(\tilde{X}\hat{\Lambda}) &= \sqrt{\frac{(\tilde{X}\hat{\Lambda})'(\tilde{X}\hat{\Lambda})}{T}} \\ &= \sqrt{(\hat{\Lambda}'\hat{\Lambda})^2 \left(\frac{\widehat{FCI}'\widehat{FCI}}{T} \right)} \\ &= \hat{\Lambda}'\hat{\Lambda} \end{aligned} \quad (\text{A.3})$$

where in the second equality, we use expression (A.1) and $\hat{U}\hat{\Lambda} = \mathbf{0}$, and in the last equality we used the identifying restriction $T^{-1} \sum_{t=1}^T \widehat{fci}_t^2 = \widehat{FCI}'\widehat{FCI}/T = 1$. After replacing equation (A.3) in (A.2) yields the expression for the FCI established in (4).

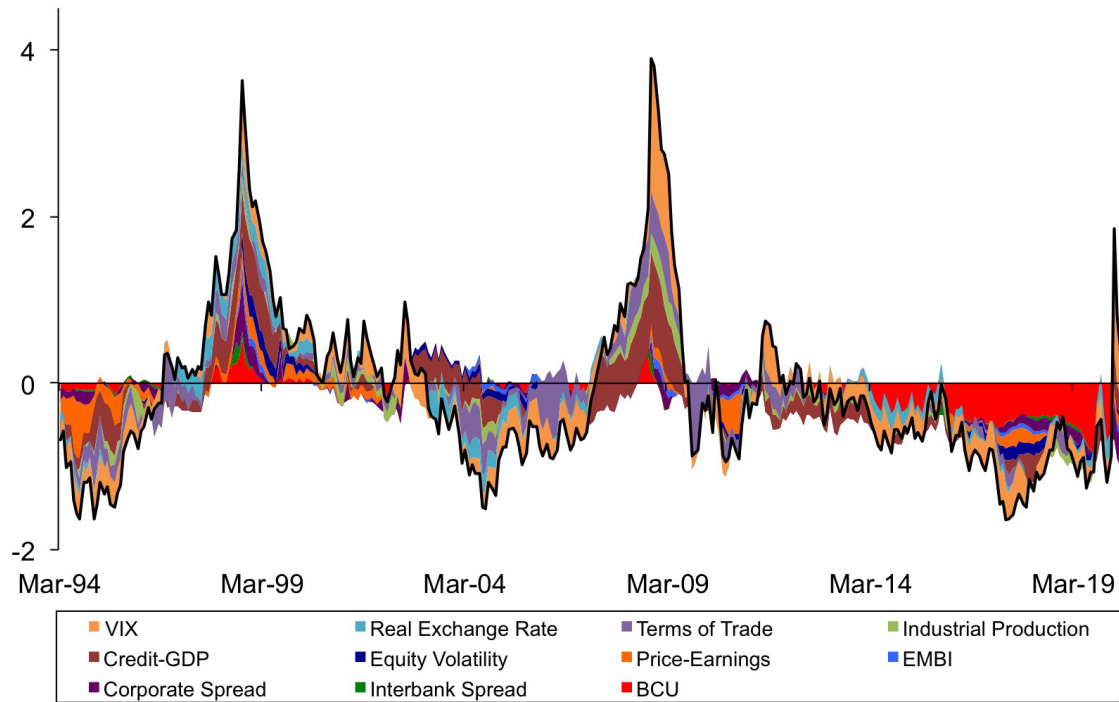
Figure 1: Financial Conditions Index for Chile



Financial Condition Index computed under alternative standardization as described in the main text. Shaded areas mark periods of substantial financial market distress, as mentioned in the labels. Asian crisis comprises the period from July 1997 to July 1999, Dot-com episode occurred in September 2002, Global financial crisis includes the period from June 2007 to August 2009, the peak of European crisis occurred during August 2011, turbulences in China's financial market occurred during December 2015, most relevant effects of Civil protests and riots comprises the period from October 2019 to December 2019, and the impacts of the COVID-19 pandemic occurred from March 2020 onwards.

Source: Authors' elaboration.

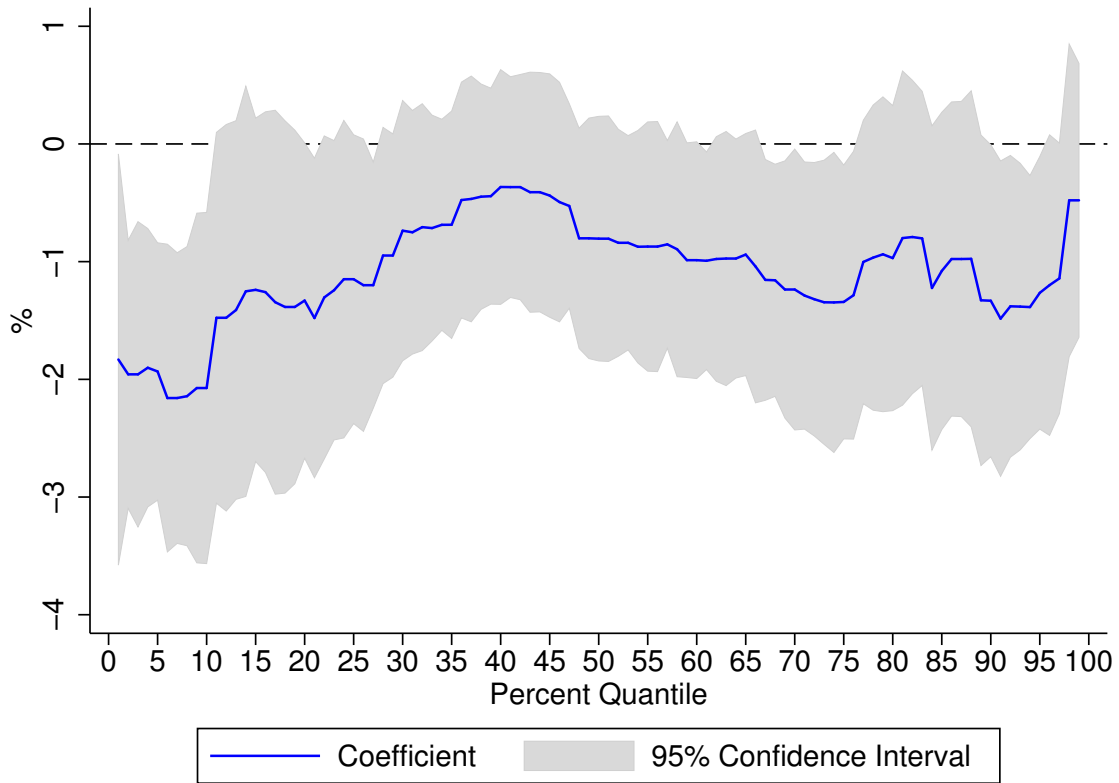
Figure 2: Contribution of Macro-Financial Variables to FCI



Decomposition of the FCI under the base standardization.

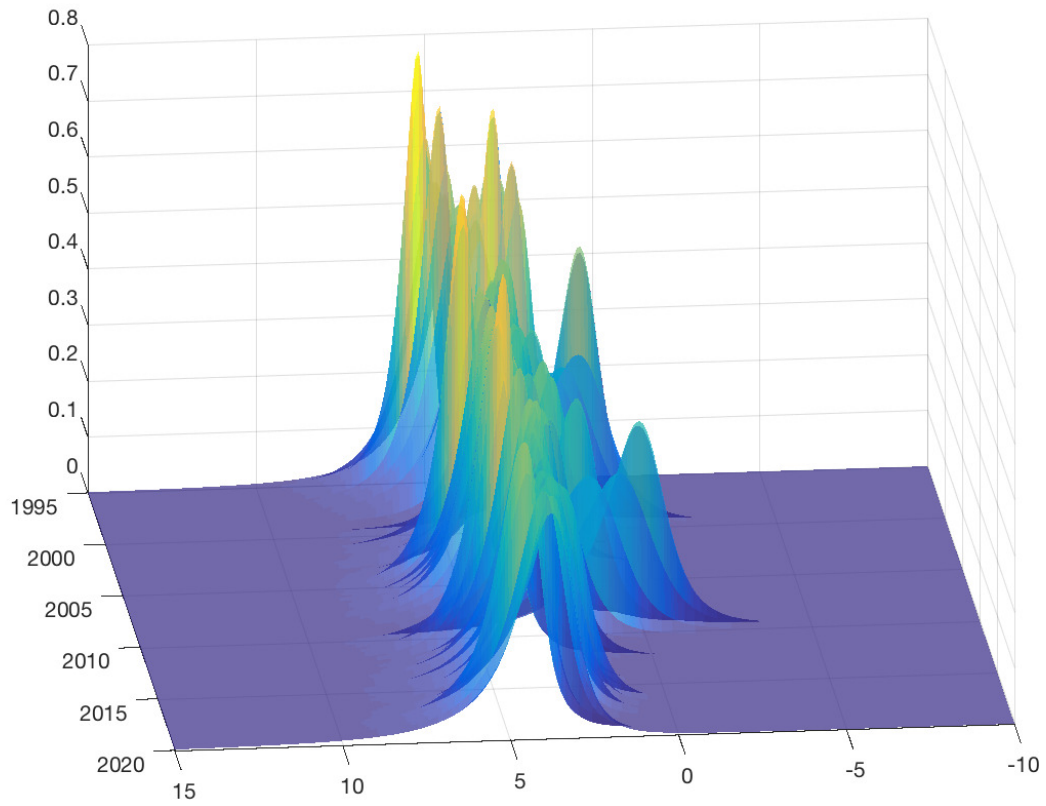
Source: Authors' elaboration.

Figure 3: FCI Effects on One-Year-Ahead GDP Growth Forecast by Quantile



Bootstrapped confidence intervals considering 150 replications.
Source: Authors' elaboration.

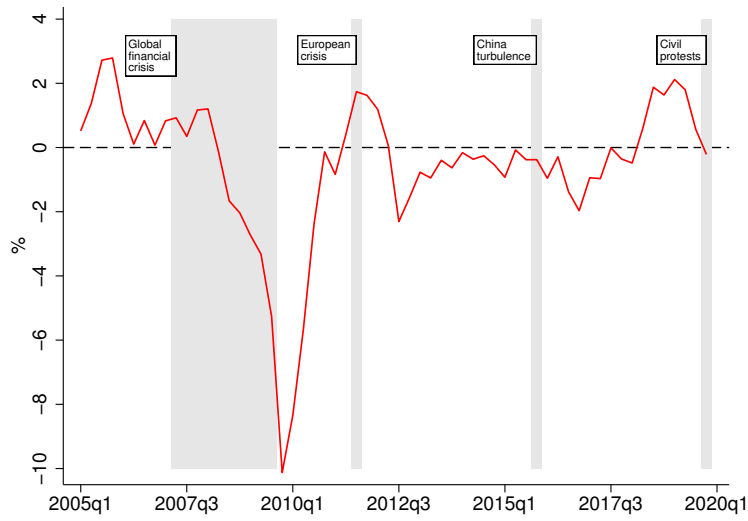
Figure 4: Distribution of Future GDP Growth over Time



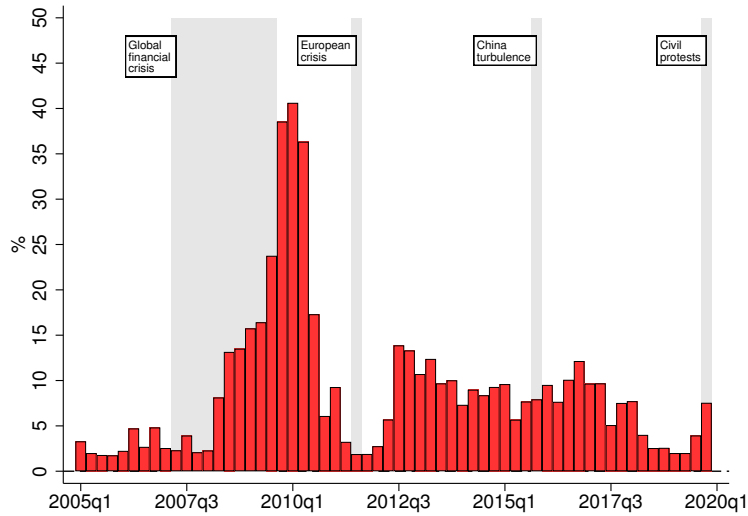
One-year-ahead GDP growth distribution, conditional on current GDP growth and FCI.
Source: Authors' elaboration.

Figure 5: Growth at Risk for Chile

(a) 5th Percentile of Future GDP Growth over Time



(b) Probability of Future Negative GDP Growth



5th percent quantiles and probabilities of negative GDP growth were computed from the predicted quantiles of model (1). Shaded areas mark periods of substantial financial market distress, as mentioned in the labels. Global financial crisis comprises the period from 2007q2 to 2009q3, the peak of European crisis occurred during 2011q3, turbulences in China's financial market occurred during 2015q4, and most relevant effects of Civil protests and riots comprises the last quarter of 2019.

Source: Authors' elaboration.

Table 1: Variables for the FCI Computation

Variable	Description	Source
r_t^s	Yield of 10-years sovereign inflation-indexed bond (BCU)	CBC
s_t^s	Spread between interest rate on deposits and 3-months sovereign rate	CBC
s_t^c	Spread between corporate and sovereign bonds real interest rates	BB
$embi_t$	EMBI Chile	BB
PE_t	Price to earnings of local stock market index (IPSA)	BB
σ_t	Volatility of local stock market index (IPSA)	BB
CY_t	Credit to GDP gap	Martinez et al. (2018)
ipi_t	Annual change of industrial production index	INE
tot_t	Annual change of terms of trade	CBC
e_t	Real exchange rate	CBC
vix_t	CBOE implied volatility index (VIX)	BB

CBC: Central Bank of Chile; BB: Bloomberg; INE: National Statistics Institute; CBOE: Chicago Board Options Exchange.
 Source: Authors' elaboration.

Table 2: Sensitivities of Macro-Financial Variables to the FCI

Variable	Sensitivity	95% CI
r_t^s	0.423	[0.398 , 0.447]
s_t^s	0.120	[0.050 , 0.190]
s_t^c	0.479	[0.388 , 0.569]
$embt_t$	0.204	[0.100 , 0.309]
PE_t	-0.648	[-0.796 , -0.500]
σ_t	0.290	[0.075 , 0.504]
CY_t	0.847	[0.828 , 0.866]
ipi_t	-0.334	[-0.386 , -0.283]
tot_t	-0.638	[-0.784 , -0.492]
e_t	-0.525	[-0.600 , -0.451]
vix_t	0.773	[0.727 , 0.819]

Sensitivities correspond to the PCA loadings of the macro-financial variables during the period between March 1994 to December 2005. Confidence intervals are computed using the asymptotic distribution derived by [Bai and Ng \(2008\)](#).

Source: Authors' elaboration.

Table 3: Descriptive Statistics of FCI Measures

	No Crisis	Crisis	Full Sample
		Panel A. FCI_1	
Mean	-0.466	1.312	-0.117
Std. Dev.	0.585	1.028	0.990
Skewness	0.156	0.522	1.307
Kurtosis	2.407	3.184	5.266
Autocorr.	0.906	0.813	0.948
		Panel B. FCI_2	
Mean	-0.427	1.327	-0.083
Std. Dev.	0.585	1.067	0.991
Skewness	0.051	0.520	1.335
Kurtosis	2.307	2.924	5.437
Autocorr.	0.893	0.790	0.941
		Panel C. FCI_3	
Mean	-0.539	1.131	-0.211
Std. Dev.	0.518	1.115	0.947
Skewness	0.248	0.861	1.723
Kurtosis	2.683	3.451	7.169
Autocorr.	0.852	0.821	0.928

FCI_1 , FCI_2 , and FCI_3 stand for the Financial Conditions Index computed under the standard aggregation, real-time aggregation, and real-time with equal weights aggregation, respectively.

Source: Authors' elaboration.

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