Growth at Risk and Macroeconomic Uncertainty in Mexico*

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Abstract

In this paper, we analyze the impact of uncertainty on the distribution of economic growth in Mexico through the methodology of Growth at Risk. This analysis is carried out in two stages: first, we estimate a quantile regression of annual output growth conditional on macroeconomic uncertainty and and other determinants of the distribution of output growth, such as financial conditions. In the second stage, based on the fitted values of the quantile regression, we estimate the parameters of a $t-skewed$ distribution by semiparametric methods. Our results show that uncertainty contributes to identify the negative bias of growth expectations. In particular, the impact of uncertainty is negative and statistically significant on the left tail of the distribution. These results suggest that an increase in uncertainty results in a downward bias for growth expectations, i.e. the estimated distribution increases its dispersion and shifts to the left, which leads to an increase of the probability of observing lower levels of growth. Our results are robust to contidioning on measures of financial conditions, uncertainty, and risk exposure, as well as to the use of alternative variables of economic activity.

Key words: Macroeconomic Uncertainty; Financial Conditions; Growth at Risk.
JEL Classification: C53, E23, E27, E32, O40.

1 Introduction

The Mexican economy has been exposed to several episodes of high uncertainty associated with both internal and external factors that have had a significant impact on economic performance. In particular, the recent COVID-19 Pandemic has affected global economic activity, labor markets and financial markets, and their remains significant uncertainty regarding its evolution and longer-term repercussions (i.e. scarring effects). Unlike previous economic crises, such as the Mexican Peso Crisis of 1994 and the Great Financial Crisis of 2008, the

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COVID-19 Pandemic has its origin in a health emergency that, although not an fully economic phenomenon, has deeply impacted the global economy through both supply and the demand sides of the economy with a profound impact on the evolution of financial markets. The evolution of this health crisis has occurred in an uncertain context regarding its duration, the emergence of new and more contagious variants of the virus, and the development, production and distribution of effective vaccines. In this way, economic recovery around the world has evolved in a context of high uncertainty with heterogeneity both across countries and sectors of activity. According to the above, this crisis has represented an important challenge for researchers and policymakers regarding the design of effective policies for the recovery.

This paper contributes to the existing literature on the analysis of the empirical relationship between macroeconomic uncertainty and expectations of economic growth in Mexico. In particular, this analysis is carried out through the Growth at Risk (GaR) methodology proposed by Adrian et al. (2019). Our research is specially relevant for the study of economic crises, and, specifically, for the COVID-19 Pandemic, which has been characterized by high levels of uncertainty. Related literature has emphasized the role of uncertainty as an important determinant of economic growth and expectations (Bloom (2009); Bloom (2014); Bonciani and Jason (2019); Jovanovic and Ma (2020); Gu et al. (2021)). In this sense, an environment of high uncertainty can impact decision-making, with adverse effects at both the micro and macro levels, and in particular in financial markets. For example:

- Firms may delay their investment and hiring plans as a result of the expectation of lower returns;
- Households could increase their savings, and therefore reduce their consumption; and
- The cost of financing could increase significantly given the expectation of higher risk premiums.

According to the above, it is reasonable to assume that uncertainty could affect not only point estimates of economic growth, but also its entire probability distribution, generating a bias in expectations of economic activity (Adrian et al. (2019); Prasad et al. (2019)). Thus, it seems relevant that most policymakers, such as central banks and international organizations, provide not only specific estimates of the mean or median GDP growth and other economic variables of interest, but also a detailed analysis of the balance of risks around a central scenario, thereby emphasizing the importance of the shape of conditional growth distribution.

Adrian et al. (2019) were of the first to analyze the determinants of the negative bias of United States (US) GDP growth expectations by empirically modeling the probability distribution of expected GDP growth as a function of observable economic conditions and financial conditions in the economy. To approximate the financial conditions in the US, they used the National Financial Conditions Index (NFCI) published by the Federal Reserve Bank of Chicago. The authors find that the estimates of the first quantiles of the GDP growth distribution have greater variability depending on the state of financial conditions compared to central moments and quantiles of the upper part of the distribution. In addition, Adrian et al., 2019 proposes some measures to quantify, both downwards and upwards vulnerability of expected GDP growth.

In a related analysis Banxico (2019) and Banxico (2020a) discuss the risks for economic growth in Mexico associated with the prevailing financial conditions. [1] In particular, Banxico (2020a) focuses on the period of the COVID-19 Pandemic and finds that the estimated distribution of conditional growth, measured by the Global Indicator of Economic Activity (IGAE, for its acronym in Spanish), shifted to the left as a result of tightening of financial conditions and the slowdown in economic activity in Mexico.

Although these studies show some evidence regarding the impact of financial conditions on the distribution of economic growth in Mexico, it is possible that their results were derived totally or partially from the impact of other omitted determinants in the analysis, such as the level of uncertainty in the economy. Hence, these estimates could be biased by a problem of omitted variables if the proxy for financial conditions of the economy reflects the effect of uncertainty, both internal and external[2], on economic growth. In particular, in an environment of greater uncertainty, more restrictive credit and liquidity conditions could be faced by firms and households. There could be a tightening of conditions for obtaining a credit, such as a greater aversion of banks to grant loans and higher costs of access to credit that could affect the performance of economic activity. In addition, it is also possible that financial variables are not entirely adequate to analyze the expectations of economic growth. In a recent paper, Plagborg-Møller et al. (2020) show evidence that financial variables have very limited predictive power for the distribution of US GDP growth over short horizons, especially, but not limited to, the underlying risk in the left tail of the distribution.

Given that uncertainty seems to be an important omitted variable to study the distribution of economic activity, we analyze the impact of uncertainty on the expectations of economic growth in Mexico. As a measure of uncertainty, we use the Macroeconomic Uncertainty Index for Mexico (MUI) estimated by Bank of Mexico [3] based on the methodology of Jurado et al. (2015). In order to analyze the empirical relationship between macroeconomic uncertainty and the distribution of growth in Mexico, a GaR type analysis is carried out that relates the annual growth rate of the IGAE [4] with the MUI and other determinants of growth. To do this, following Adrian et al. (2019), a two-stage estimation is performed. First, a quantile regression is estimated between the annual growth rate of the IGAE, the MUI and other drivers of economic activity in Mexico such as the US industrial production index (IPUS) and inflation.[5] These estimates allow us to analyze the marginal impact of uncertainty along the conditional distribution of growth for each period of the sample.[6] In the second stage of

[1]These analyzes use a non-public financial conditions index estimated by Bank of Mexico.

[2]In this regard, it can be shown that the NFCI and a Financial Conditions Index (FCI) for the Mexican economy proposed by Carrillo and García (2021) have a high positive correlation since 2009, that could reflect the effect of external uncertainty on financial conditions in Mexico.

[3]It should be noted that this series is not for public use and was requested from the Central Bank for the analysis of this paper.

[4]The IGAE is a monthly series that measures aggregate (real) economic activity. Being highly correlated with GDP, it is sometimes referred to as the monthly GDP. This variable is used for our main analysis, instead of GDP, since the MUI was constructed for a monthly frequency in order to better capture the state and variations of uncertainty in the economy.

[5]The Appendix C presents the results of our estimates based on GDP, aggregating the monthly variables of the model through a simple mean. Our main conclusions remain in the face of the change in the measurement of economic activity and in the frequency of the data.

[6]Unlike ordinary least squares estimates, quantile regression is estimated at the different quantiles of the distribution of the dependent variable and not just at a central moment, so it is more robust to the presence of

the methodology, the parameters of a $skewed-t$ distribution of output growth are estimated based on the fitted values of the quantile regression. This distribution allows us to have a more complete analysis of the dispersion and bias of the conditional distribution of growth, as well as to calculate the probabilities associated with different levels of growth and to measure the impact of uncertainty on the bias of growth expectations.

Our results suggest that a higher level of uncertainty increases the downside risks of expected economic growth of the Mexican economy. Our estimates show that uncertainty has a negative and statistically significant effect on the lower quantiles of the growth distribution, a moderate effect on the central moments, and a not significant effect on the right side of the distribution. Furthermore, these estimates seem particularly suitable for analyzing the negative bias of growth expectations during periods of economic crisis. It is shown that in periods of recession, during which uncertainty significantly increases, the MUI contributes to estimate a distribution of expected growth which attributes a greater probability of observing low and negative economic growth levels. It should be noted that this empirical relationship seems to be more structural and valid both during episodes of high uncertainty and in those that are more stable.

Our analysis is closely related to the works of Jovanovic and Ma (2020) and Gu et al. (2021), that, through the GaR methodology, analyze the impact of uncertainty on the distribution of economic growth in the US and China, respectively. On the one hand, Jovanovic and Ma (2020) show, similar to our results, that higher macroeconomic uncertainty is associated with a distribution of output growth that is more spread out, and in which an increase in uncertainty leads to a sharp decline in the lower tail of growth distribution, and a much smaller and insignificant impact on its upper tail. On the other hand, Gu et al. (2021) investigates the impact of economic policy uncertainty (EPU) on economic activity in China. These authors find that the UPE alters the skewness and kurtosis of the distribution, leading to a greater negative skew of the growth distribution.

Our results are robust when the MUI is included along with other measures of uncertainty, associated with both internal and external factors, and when we control for measures of risk and financial conditions in Mexico. In particular, our results remain significant when controlling for the US NFCI and the Mexican FCI (Carrillo and García (2021)). We also find that our estimates remain valid when including the Mexican EPU, the global EPU and the US EPU. Similar results are found when we include other more traditional measures of risk and uncertainty such as changes in the real and nominal exchange rate as well as the risk premium.

In addition, we perform robustness tests to determine whether our results are robust to using alternative measures of economic activity. For these exercises we use six indicators. On the demand side, we include gross fixed investment and private consumption. On the supply side, we include the monthly indicator of industrial activity and the IGAE of the tertiary sector. Finally, on the labor market side, we use the level of formal employment in the economy as a whole, measured through the number of jobs affiliated with the IMSS[7] and the employment rate. For all these exercises we find an impact of uncertainty on productive activity similar to the one estimated based on the IGAE for the economy as a whole.

extreme values.

[7]The Instituto Mexicano del Seguro Social (IMSS) is an institution that provides social security for workers. All formal private sector workers who receive a salary are required, by law, to register with IMSS.

Finally, we provide a more detailed analysis of the impact of uncertainty on the distribution of economic growth during the periods of the Mexican Peso Crisis of 1994, the Great Financial Crisis of 2008, and the COVID-19 Pandemic. Our results reveal that, during periods characterized by deep recessions, the growth of economic activity is more similar to the estimates of the lower quantiles than to the median of the distribution of economic growth. Intuitively, during recessions output falls are accompanied by high levels of uncertainty that exacerbate the negative bias of growth projections, making the central moments of the estimated distribution relatively optimistic with respect to the observed values.

The rest of the article is organized as follows. In section 2, we make a first approach to the relationship between uncertainty and economic activity in Mexico through a vector autoregressive analysis (VAR) that shows the relative importance of the MUI shocks on the dynamics of economic growth in Mexico. In section 3, we present the methodology, general results, and robustness exercises of our GaR analysis between macroeconomic uncertainty and growth distribution of IGAE. In section 4, we analyze the results of our estimates for the particular cases of the Crisis of 1994, the Great Financial Crisis of 2008, and the COVID-19 Pandemic. Finally, in section 5 we present some general conclusions.

2 Uncertainty and Economic Activity in Mexico

To analyze the empirical relationship between uncertainty and growth, we use the Macroeconomic Uncertainty Index for Mexico (MUI) estimated by Bank of Mexico (Banxico (2020b)) based on the methodology of Jurado et al. (2015). This index is constructed as a simple mean of the variability of forecast errors for a set of N macroeconomic variables. Intuitively, an increase in the MUI shows that, on average, the difficulty for predicting the behavior of the economy at a given moment in time has increased, which is interpreted as an increase in the level of uncertainty in the economy. Formally, the MUI can be expressed as:

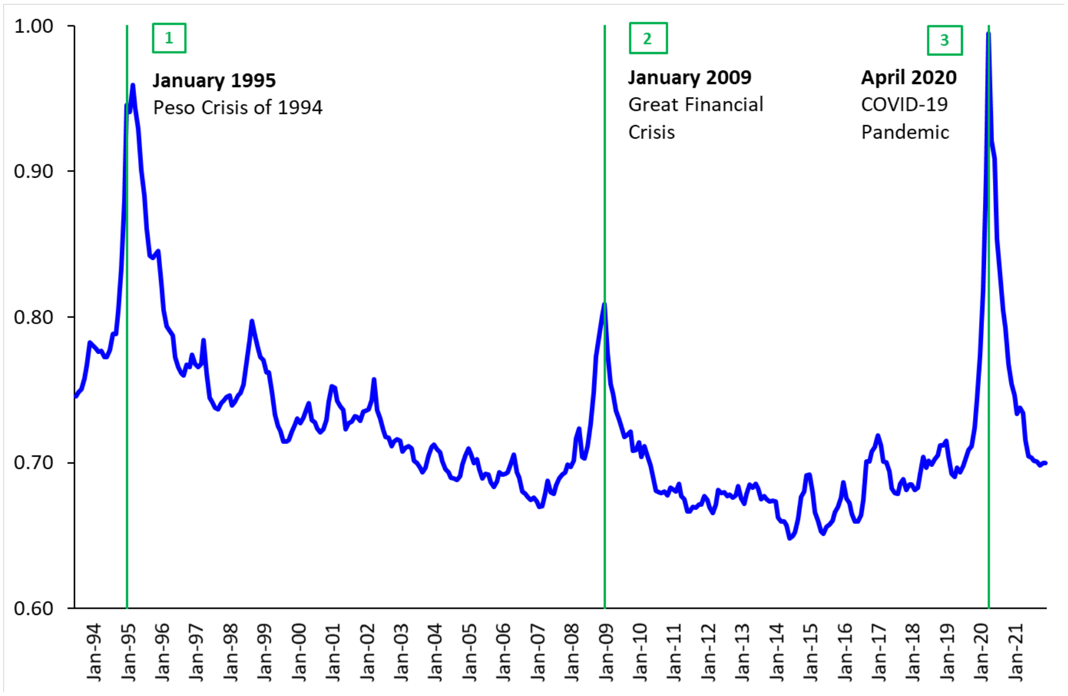
$$MUI_t^h = \frac{1}{N}\sum_{n=1}^{N} U_{n,t}^h \tag{1}$$

Where $U_{n,t}^h$ is a measure of the variability of the forecast error of the variable n, in the period t, for h forecast periods ahead. In the case of Mexico, the MUI is calculated from 125 monthly frequency series of economic activity, prices and from the foreign market (See Banxico (2020b)).

For our estimates, we consider the MUI with one-step ahead forecasts (i.e. h=1). [8] It can be identified that significant increases in the MUI are related with economic or geopolitical events that are commonly associated with an increase in the level of uncertainty. For example, it can be observed that the 1994 and 2008 crises are associated with environments of high uncertainty, as well as the period between 2015 and 2019 in which there were significant drops

[8] Our results are robust to changes in the MUI specification for 3 and 12 step-ahead forecasts. In this regard, it stands out that, in the face of longer forecast horizons, the MUI tends to a type of unconditional mean in the sense that today's information has little value for forecasting a further forecast horizon. The MUI specifications with forecast horizons that are too far away only identify the periods in which uncertainty increased significantly and persistently. According to the above, to identify the impact of uncertainty on the growth rate of the IGAE, it is convenient to use the version of the MUI with greater variability (ie $h = 1$).

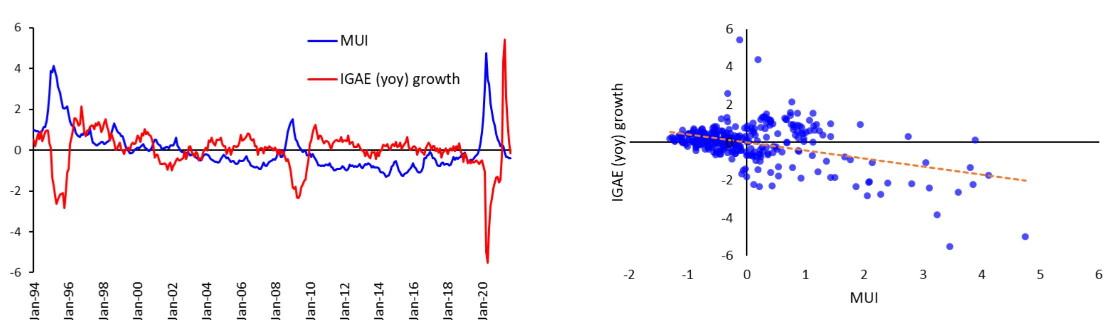
Figure 1: Macroeconomic Uncertainty Index for Mexico ($h = 1$)



Source: Own elaboration.

in oil prices, the beginning of the renegotiation process of NAFTA, and electoral processes both in Mexico and in the US (see Figure 1). More recently, since the beginning of 2020, a significant increase in the level of uncertainty associated with the COVID-19 Pandemic has been observed. According to the MUI, in April 2020 the Mexican economy reached a maximum level of uncertainty that, although it has decreased as a result of the development, production and distribution of vaccines and the gradual re-opening of the economy, it still remains at relatively high levels.

Figure 2: IGAE (yoy) growth and Macroeconomic Uncertainty Index for Mexico



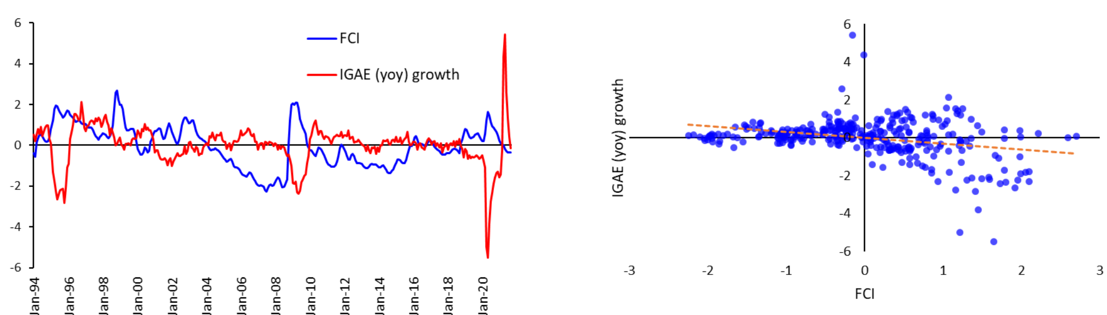
Source: Own elaboration.
Notes: To facilitate comparison, both series are standarized.

As can be observed in Figure 2, sharp drops in economic growth are accompanied by high levels of macroeconomic uncertainty. Thus, the purpose of this paper is to analyze the empirical relationship between economic growth and uncertainty, since from a theoretical and empirical point of view it has been found that uncertainty is an important determinant of growth. [9]

In this regard, several studies have analyzed the impact of uncertainty on growth through Vector Autoregressive (VAR) models (see Baker et al. (2016), Baker et al. (2020), Bloom (2009), Bonciani and Jason (2019), and ECB (2016), Gieseck and Rujin (2020)). In this type of analysis, real, nominal and financial variables are combined. These indicators are related to the level of economic activity, financial conditions, the level of uncertainty and the exposure to risk of the economy. It should be noted that financial conditions could also be relevant to analyze the negative bias of growth expectations (Adrian et al. (2019) and Banxico (2019, 2020a)).

In order to analyze the impact of uncertainty on growth, controlling for financial conditions in Mexico, we include in our analysis the Financial Conditions Index (FCI) proposed by Carrillo and García (2021).[10] These authors analyze the response of several economic activity indicators to a shock in financial conditions. According to their estimates, after a shock to financial conditions, economic activity declines in a U-shape for about twelve months. Production and consumption responses are of a similar magnitude, while investment falls to a greater extent.

Figure 3: IGAE (yoy) growth and Financial Conditions Index for Mexico



Source: Own elaboration.
Notes: To facilitate comparison, both series are standarized.

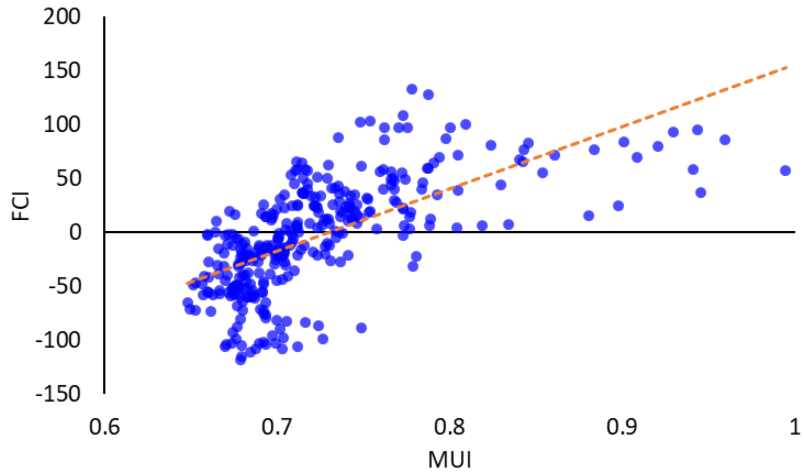
In addition to the correlation that seems to exist between the FCI and growth (see Figure 3), an important positive relationship is also observed between the MUI and the FCI in Mexico (see Figure 4), that could imply that the correlation between economic growth

[9]A possible objection is that this correlation could be due to the inclusion of the IGAE as one of the indicators for the construction of the MUI. However, it is unlikely that such a relationship stems from this fact. On the one hand, the MUI is built from 125 economic series, each with the same weight, so that the relative weight of the IGAE is very small. On the other hand, the MUI is constructed as a weighted average of the forecast errors of each of the series, so this indicator, strictly speaking, bears little relation to the level of growth.

[10]These authors calculate their FCI following a methodology similar to the one proposed by Hatzius and Stehn (2018) and Koop and Korobilis (2014). In particular, they estimate a dynamic factor model using a Kalman filter adjusted for the presence of unobserved values and unbalanced sample for all variables included in the model. These variables are divided into seven categories: currencies, stocks, debt, uncertainty, country risk, commodity prices, and economic activity.

and the MUI could be implicitly derived from the relationship between growth and financial conditions.[11]

Figure 4: Financial Conditions Index and Macroeconomic Uncertainty Index, for Mexico



Source: Own elaboration.

In order to further analyze the relationship between growth, uncertainty and financial conditions in Mexico, we estimate a VAR similar to the one proposed by Bonciani and Jason (2019) and analyze the impulse-response functions (IRF) , the historical decomposition (HD), and the forecast error variance decomposition (FEVD) of the model. The shocks of the model are identified through a Cholesky identification. The VAR is estimated for eight endogenous variables in the following order: the Wu and Xia (2016) shadow interest rate as a proxy for the US Federal Reserve (FED) rate, the FCI, the MUI, the Nominal Exchange (TNE), the IGAE, the Monthly Indicator of Private Consumption (PCI), the Monthly Indicator of Gross Fixed Investment (GFI) and the CETES rate of government securities (CETES). [12] The ordering of endogenous variables for the Cholesky identification implies that the FED is the most exogenous variable in the model, since Mexico is considered a small open economy. In addition, we assume that the uncertainty measured by the MUI is affected contemporaneously by the FCI shocks, but not by the other macroeconomic variables included in the analysis.[13] All variables are included in annual growth rates, with the exception of FED, CETES, FCI

[11]Banxico (2019, 2020a) present evidence about the impact of financial conditions on the distribution of GDP growth in Mexico in a framework similar to the one proposed by Adrian et al. (2019), using in both a Financial Condition Index provided by Bank of Mexico different from the one proposed by Carrillo and García (2021). In Appendix D, following the framework proposed by Banxico (2019, 2020a), we carried out an exercise with the GaR methodology between the IGAE, the FCI proposed by Carrillo and García (2021) and the annual inflation rate, finding similar results.

[12]In a Box from the Quarterly Report October – December 2019, Banxico (2019) analyzes the effect of uncertainty on consumption and investment in Mexico by estimating two VAR models, one for consumption and the other for investment.

[13]With the order of identification of the variables, we assume that the FCI is relatively more exogenous than the MUI in the sense that shocks to the FCI affect the MUI contemporaneously, but shocks to the MUI do not affect the FCI contemporaneously. It is clear that this assumption is restrictive and it could be suggested that an order in which it is assumed that the uncertainty is more exogenous than the financial conditions is more

and MUI. The VAR is estimated for three lags, identified through the Akaike information criterion. In addition, the IRF and FEVD are calculated for a horizon of three years ahead (ie, 36 months).

The impulse-response functions of the VAR between IGAE growth, MUI, and the rest of the endogenous variables show evidence of a negative and statistically significant effect of uncertainty on economic growth.[14] In particular, the effect of a shock of one standard deviation (sd) in uncertainty has a negative effect on IGAE growth of about 0.5 sd and remains statistically different from zero for about 11 months. In Figure 5 we present the IRF of the endogenous variables of the model after a shock in MUI. The direction in which the variables respond is consistent with the exercise hypothesis; for example, the FED does not change in the face of shocks from uncertainty in Mexico because it is an exogenous variable, while the exchange rate increases significantly. On the other hand, private consumption falls in almost the same proportion as the IGAE, while the gross fixed investment falls in a greater extent. These latest results are consistent with those found by Banxico (2020a) and Bonciani and Jason (2019).

The HDs provide evidence about the incidence of each shock on the variation of economic activity. As can be seen in Figure 6, during the period of the COVID-19 Pandemic between April 2020 and December 2020, more than half of the negative variation of the IGAE ccan be attributed to uncertainty in Mexico, highlighting the relatively low contribution of financial conditions.[15] Compared to other deep crises such as those of 1994 and 2008, it is interesting to note that although uncertainty explains a significant proportion of the fall in production, it is relatively less important than other shocks.

Finally, according to FEVD estimates (see Figure 7), after 36 months around 25% of IGAE growth is explained by uncertainty shocks, while production shocks explain about 43%. In contrast, FCI shocks explain only a small proportion of the variance of the growth forecast error. Bonciani and Jason (2019) present similar results to ours for the US economy. Likewise, for the case of Mexico, Banxico (2019) analyzes the impact of MUI on investment and consumption, finding also similar results.[16]

In the next section, we analyze the empirical relationship between macroeconomic uncertainty and the distribution of expected economic growth in Mexico. In particular, based on Adrian et al. (2019), we apply a GaR model to semiparametrically estimate the distribution of expected IGAE growth as a function of uncertainty and other explanatory variables. As an additional exercise, as in the VAR model analyzed in this section, we also control for the FCI of Carrillo and García (2021), in order to determine if the relationship between uncertainty and economic growth is robust to the inclusion of a financial condition indicator.

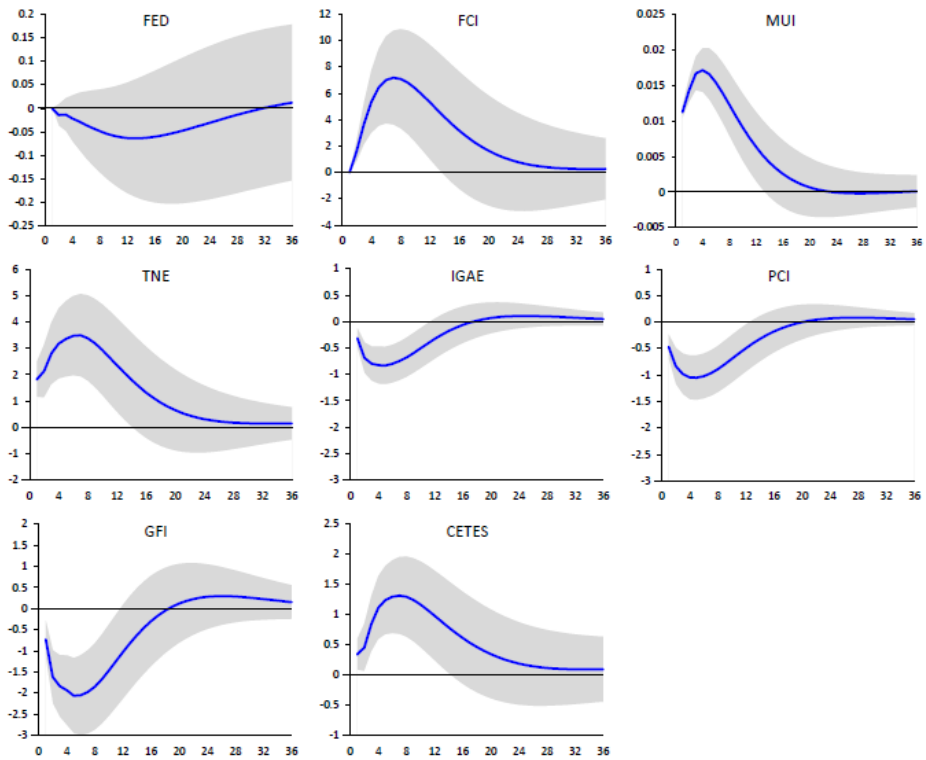
appropriate. Given the above, in the Appendix A we present the results for a VAR specification in which the Cholesky ordering for the FCI and the MUI is interchanged, reaching similar results.

[14]On the other hand, we did not find a effect significantly different from zero of the FCI on IGAE annual growth. This result does not necessarily imply that the FCI is not an important determinant of growth, since the relevant information that this contains could be more useful in explaining other moments of the growth distribution different to the mean.

[15]This result also holds under Cholesky's alternative identification where uncertainty is considered relatively more exogenous than the FCI.

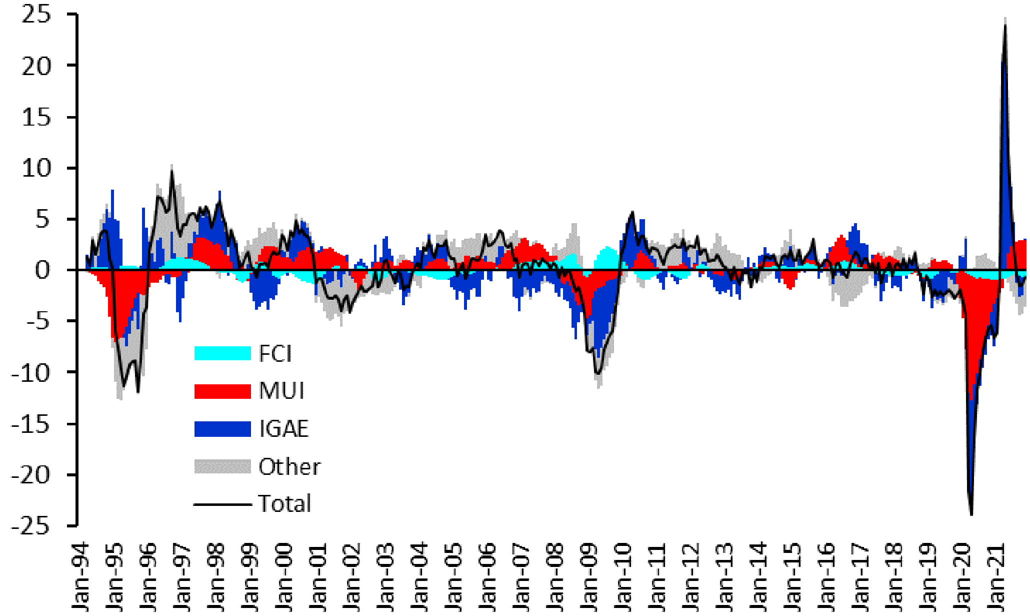
[16]However, unlike the previous approaches, in our analysis we also control for financial conditions in Mexico in order to identify the effect of uncertainty on the dynamics of economic activity.

Figure 5: Response to Cholesky One S.D. (d.f. adjusted) Innovations to MUI



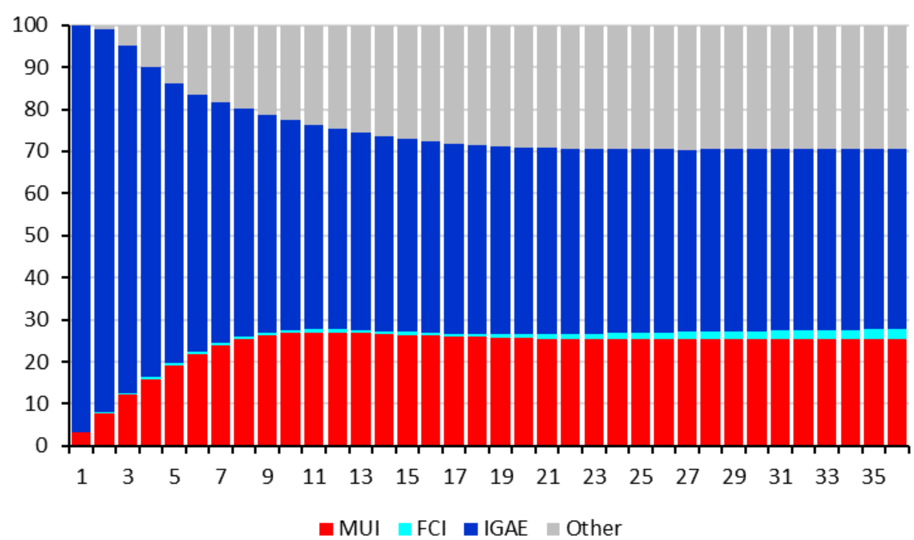
Source: Own elaboration.
Notes: Shaded areas represent $\pm$ 2 S.E. confidence intervals.

Figure 6: Historical Decomposition of IGAE (yoy) growth



Source: Own elaboration.
Notes: Other is the aggregated contribution of FED, TNE, PCI, GFI, CETES.

Figure 7: Forecast Error Variance Decomposition of IGAE (yoy) growth



Source: Own elaboration.
Notes: Other is the aggregated contribution of FED, TNE, PCI, GFI, CETES.

3 Growth at Risk and Macroeconomic Uncertainty in Mexico

3.1 Growth at Risk Methodology

In the previous section we showed evidence that the annual growth of IGAE responds negatively, and in a statistically significant way, to MUI shocks in Mexico. Although these results are robust to the inclusion of other determinants of growth such as the FCI (Carrillo and García (2021)), according to Adrian et al. (2019) this type of point estimate tends to ignore the negative bias of growth expectations, thus it is more convenient to have an estimate of the entire conditional distribution to evaluate the impact of its determinants.

To estimate a conditional distribution of expected economic growth in Mexico, and to assess the role of uncertainty, we use the two-stage methodology of Adrian et al. (2019). According to this methodology, in the first stage a quantile regression is estimated between the expected annual growth of production and a set of control variables. These estimates allow us to analyze the marginal impact of the determinants of growth along their conditional distribution for each period of the sample. In the second stage of the methodology, the parameters of a $skewed - t$ distribution of output growth are estimated based on the fitted values of the quantile regression.

3.1.1 First Step of GaR Methodology

In general, the quantile function corresponds to the inverse of the distribution function in such a way that it maps the value of the random variable for which the cumulative probability is less than or equal to the value of a given quantile. Formally, given a cumulative distribution function $F\colon \Re \to [0,1]$, and a quantile τ, the quantile function F^{-1} returns the value x such that $F(x) = P[X \leq x] = \tau$. In this way the quantile function F^{-1} is defined as:

$$F^{-1}(\tau) = inf\left\{x \in \Re\colon \tau \leq F(x)\right\} \tag{2}$$

Hence, under the assumption that the quantile function of y_{t+h}, conditional on the explanatory variables x_t, is linear in the parameters β_τ, ie $Q_{y_{t+h}|x_t}(\tau \mid x_t) = x_t\beta_\tau$, in a quantile regression the slope of the regression β_τ minimizes the weighted absolute value of the error $\epsilon_{t+h} = y_{t+h} - x_t\beta$ for each quantile τ, that is:

$$\hat{\beta}_\tau = argmin \sum_{t=1}^{T-h} \left(\tau * 1_{(y_{t+h} \geq x_t\beta)} \left|y_{t+h} - x_t\beta\right| + (1-\tau) * 1_{(y_{t+h} < x_t\beta)} \left|y_{t+h} - x_t\beta\right|\right) \tag{3}$$

Where h represents the number of forecast periods ahead for the growth forecast, T indicates the number of observations, τ represents the quantile being estimated, and $1_{(\bullet)}$ is an indicator function. The fitted value of the quantile regression of y_{t+h} conditional on x_t is defined as:

$$\hat{Q}_{y_{t+h}|x_t}(\tau \mid x_t) = x_t\hat{\beta}_\tau \tag{4}$$

Thus, $\hat{Q}_{y_{t+h}|x_t}(\tau \mid x_t) = x_t\hat{\beta}_\tau$, for a given quantile τ, corresponds to the linear estimate of the inverse of the discrete cumulative distribution function of IGAE annual growth rate conditional on determinants x_t. [17,18] Thus, the estimated coefficients of the quantile regression can be interpreted as the marginal effect of uncertainty and other determinants on the estimated discrete distribution of expected IGAE growth for a given quantile. Hence, it is possible to determine whether these effects are asymmetric throughout the growth distribution, in the sense that they present differentiated marginal effects for each quantile of the distribution. In particular, we say that an explanatory variable contributes to the negative bias of growth distribution if it presents negative and statistically significant marginal effects on the left region of the growth distribution that are greater, in absolute value, than those estimated for central moments and the right region of the distribution.

Although the quantile regression estimates are useful for analyzing the impact of explanatory variables on the conditional distribution of expected growth, they do not allow us to analyze other indicators related to the bias and dispersion of growth expectations, as well as to calculate the probability of observing growth rates below certain levels of activity, and other measures that allow us to make a comparison of distributions such as the relative entropy. The second part of the Adrian et al. (2019) methodology allows us to estimate a continuous growth distribution function from the quantile regression estimates.

3.1.2 Second Part of GaR Methodology

In general, from the fitted valued of the quantile regressions, $\hat{Q}_{y_{t+h}|x_t}(\tau \mid x_t) = x_t\hat{\beta}_\tau$, it is possible to estimate the parameters of a continuous probability distribution function. Specifically, it is possible to choose the parameters ψ_{t+h} for the period t and the forecast horizon h in such a way as to minimize the quadratic distance between the estimated quantile function and the inverse of a continuous cumulative distribution function, that is,

$$\left\{\hat{\psi}_{t+h}\right\} = argmin \sum_{\tau} \left(\hat{Q}_{y_{t+h}|x_t}(\tau \mid x_t) - F^{-1}(\tau;\psi)\right)^2 \tag{5}$$

According to Adrian et al. (2019), the $skewed - t$ distribution is useful for adjusting the estimates of the previous quantile regression because it allows for biases and asymmetric tails of the distribution. This grants a more comprehensive analysis of the impact of uncertainty on the negative bias of growth expectations. Formally, the $skewed - t$ distribution is a general form of the t distribution whose density function depends on four parameters and it is expressed as follows:

[17] According to Koenker and Bassett (1978), $\hat{Q}_{y_{t+h}|x_t}(\tau \mid x_t) = x_t\hat{\beta}_\tau$ is a consistent linear estimator of the quantile function y_{t+h} conditional on x_t.

[18] Unlike ordinary least squares estimation where a consistent linear estimate of y_{t+h} conditional on x_t is obtained from minimization of the sum of squared errors $\epsilon_{t+h} = y_{t+h} - x_t\beta$, the quantile regression is estimated at each quantile of the distribution of the dependent variable and not only at a central moment, so it is more robust to the presence of extreme values. In addition, the quantile regression estimates are based on the minimization of the weighted sum of absolute value errors, so the quantile regression estimate for the central moments of the growth distribution corresponds to the conditional median and not to the conditional mean.

$$f(y;\mu,\sigma,\alpha,\upsilon)=\frac{2}{\sigma}s\left(\frac{y-\mu}{\sigma};\upsilon\right)S\left(\alpha\frac{y-\mu}{\sigma}\sqrt{\frac{\upsilon+1}{\upsilon+\left(\frac{y-\mu}{\sigma}\right)^2}};\upsilon+1\right) \tag{6}$$

Where $s(\bullet)$ and $S(\bullet)$ are the density and cumulative probability functions of a t distribution, respectively.

According to the above, for each period of the sample, four parameters of the $skewed-t$ distribution are estimated by maximum likelihood.[19] The parameter μ determines the position; σ is the scale parameter; υ the degrees of freedom; and α the shape. These parameters fully characterize a continuous distribution of expected IGAE annual growth for each sample period.

In addition, by fitting a continuous distribution to the quantile regression estimates, it is possible to analyze the impact of uncertainty on growth expectations. As will be described in more detail in the next section, for this purpose two estimates of the continuous distribution of growth are made: one conditional and one unconditional on the level of uncertainty. In this way, it is possible to determine the impact of uncertainty on the expected IGAE annual growth through the comparison of those distributions.

3.2 Data and Benchmark Model

For the estimates of the GaR methodology described in the previous section, we use seasonally adjusted series for a monthly sample from July 1993 to December 2021. As a measure of economic activity in Mexico, we use the annual growth rate of IGAE from the National Institute of Statistics and Geography (INEGI, for its acronym in Spanish). As controls we use lags of the dependent variable, the level of economic activity in the US, measured through the annual growth rate of the Industrial Production Index (IPUS)[20] and annual inflation (INF) measured from the Consumer Price Index (INPC) of the INEGI. Following the GaR methodology, we analyze the impact of the MUI on different quantiles of the expected growth of the IGAE. Our Benchmark Model is estimated from the following equation:

$$y^{\tau}_{t+h}=\alpha_{\tau}+\beta_{\tau}y_t+\delta_{\tau}INF_t+\gamma_{\tau}IPUS_t+\theta_{\tau}MUI_t+\varepsilon^{\tau}_t \tag{7}$$

Where $Q_{y_{t+h}|x_t}(\tau \mid x_t)=y^{\tau}_{t+h}$, y_t is the IGAE annual growth rate, INF_t is the annual inflation, $IPUS_t$ is the annual growth rate of the IPUS, and MUI_t is the MUI with a forecast horizon of one month. The subscript h indicates the forecast horizon of the quantile regression and the superscript τ indicates the quantile being estimated, with discrete values from 0.1 to 0.9, in 0.05 intervals. For example, y^{25}_{t+3} corresponds to the 25th quantile of the growth distribution of IGAE with a forecast horizon of three months ahead.

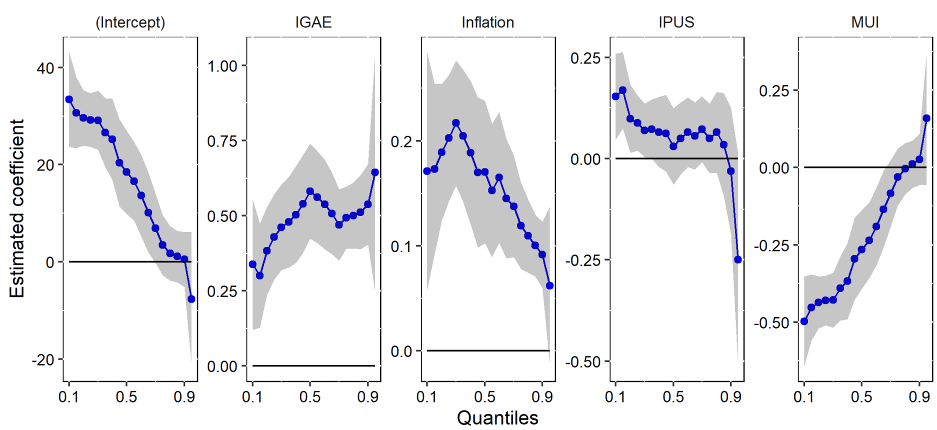
[19] All estimates of our analysis are made with the free software R, using , mainly, the packages: quantreg for the quantile regressions and ghyp and sn for semiparametric estimation of the $skewed-t$ probability functions.

[20] Board of Governors of the Federal Reserve System (US). The series is taken from the St. Louis Federal Reserve data system at https://fred.stlouisfed.org/series/INDPRO

3.3 An Analysis of the Impact of Uncertainty on the Distribution of Growth in Mexico

Figure 8 shows estimated coefficients of equation 7, for each analyzed quantile of the distribution of annual growth rate of IGAE, for a forecast horizon of three months.[21] The results show that uncertainty has a negative and statistically significant marginal effect on the left tail of the distribution of economic growth, while the impact of uncertainty on quantiles on the right region of that distribution is not statistically different from zero. Intuitively, estimated coefficients show that macroeconomic uncertainty contributes to identify the negative bias of growth expectation since the estimated distribution shows a greater variance in the left tail associated with low levels of growth and high levels of uncertainty. In particular, according to the estimated coefficients in Table 1, the marginal effect of uncertainty in the tenth quantile of estimated IGAE annual growth distribution is -0.50 percentage points (pp), higher in absolute value to the marginal effect of the MUI of -0.27 pp on the median of the distribution.

Figure 8: Quantile Regression Coefficients for the Benchmark Model (h = 3 months)



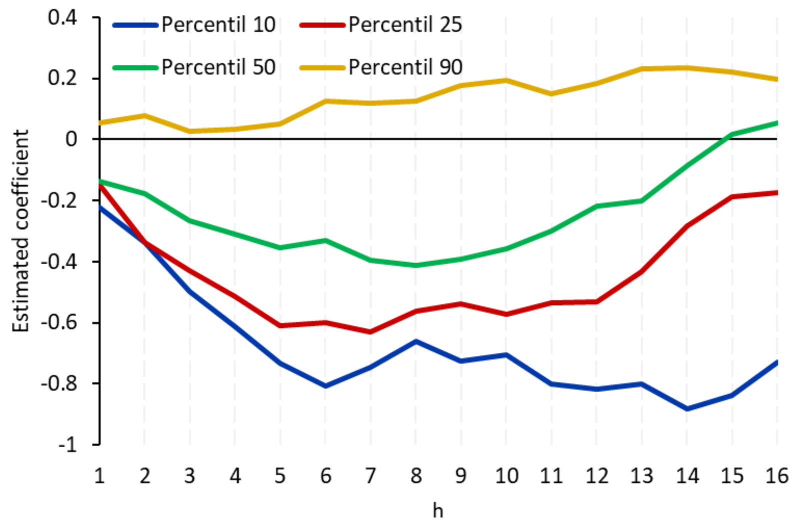
Source: Own elaboration.
Notes: Blue lines represent estimation coefficients for each quantile. 90% Confidence intervals are depicted by the grey band, built by bootstrap.

Figure 9 shows the estimated coefficients of the Benchmark Model for the MUI for several forecast horizons h. According to these estimates for forecast horizons of 1 to 15 months, the marginal effect of uncertainty on the expected IGAE growth is negative and of greater magnitude, in absolute value, for quantiles of the left tail of distribution. It should be noted that this result is similar to the one found by Jovanovic and Ma (2020) for the case of the US.

Based on our estimates of the quantile regressions, it is also possible to perform an analysis of the dispersion and bias of the growth distribution for each of the sample periods. In particular, it is of interest to determine the effect of uncertainty on the dispersion and the median of the distribution. The relationship between these two indicators allows us to analyze the effect of uncertainty on the negative bias of growth expectations, understood not only as

[21] As is usual in the literature, throughout the article we present the results corresponding to a forecast horizon of three months, equivalent to one quarter. However, we show below that our main results hold for forecast horizons of one to 15 months.

Figure 9: Estimated coefficients for MUI



Source: Own elabration.

Table 1: Estimated Coefficients of Benchmark Model (h = 3 months)

	10th Quantile			25th Quantile		
	Coef.	Lower	Upper	Coef.	Lower	Upper
Intercept	33.42 ***	23.58	43.25	29.16 ***	23.7	34.59
IGAE	0.34 **	0.12	0.56	0.43 ***	0.3	0.57
IPUS	0.15 **	0.05	0.26	0.09 **	0.0	0.16
Inflation	0.17 **	0.06	0.29	0.20 ***	0.1	0.27
MUI	-0.50 ***	-0.01	0.00	-0.43 ***	0.0	0.00

	50th Quantile			90th Quantile		
	Coef.	Lower	Upper	Coef.	Lower	Upper
Intercept	18.48 ***	9.88	27.09	0.52	-4.85	5.90
IGAE	0.58 ***	0.42	0.74	0.54 ***	0.40	0.67
IPUS	0.03	-0.07	0.12	-0.03	-0.19	0.13
Inflation	0.17 ***	0.10	0.24	0.09 ***	0.06	0.12
MUI	-0.27 ***	0.00	0.00	0.03	0.00	0.00

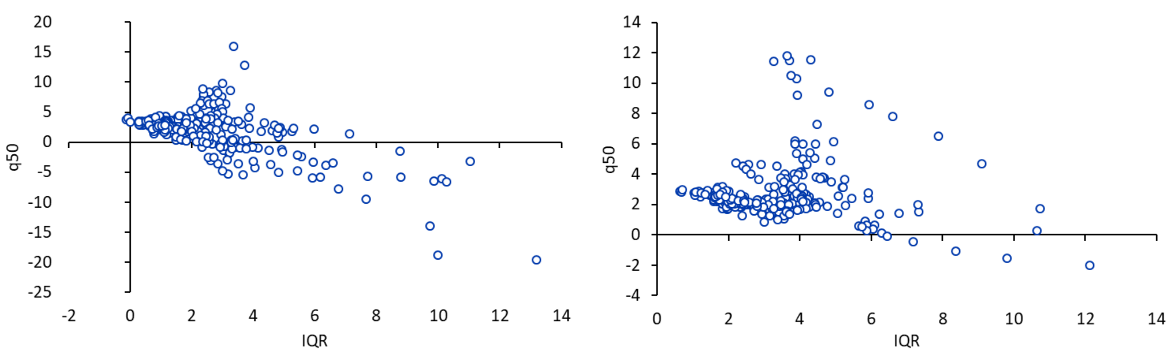
Source: Own elaboration.
Notes "***", "**", "*" if $p < 0.01$, $p < 0.05$, and $p < 0.1$, respectively. Lower and Upper indicate the 90% confidence interval built by bootstrap.

an increase in the expectation of lower levels of growth, but also as the increase of probability mass associated with low levels of growth in the face of higher levels of uncertainty in the economy.

As mentioned above, our results show that uncertainty has a negative and statistically significant effect on both the left tail and the median of expected growth distribution of IGAE.

In addition, marginal effects of uncertainty are greater, in absolute value, for the lowest quantiles. These results suggest a positive relationship between the dispersion of growth distribution and uncertainty, which, in turn, is negatively correlated with the median. Figure 10 presents the relationship between the interquartile range[22] and the median of the fitted values of the Benchmark Model (see Equation 7) for each period of the sample. The figures show a strong negative correlation between the median and the interquartile range of the conditional distribution of expected growth for forecast horizons of three and twelve months. The above evidence shows, as a whole, that with an increase in uncertainty, not only does the dispersion increase and the median of the expected growth distribution of the IGAE decreases, but there is also a shift of the distribution to the left (associated with the negative relationship between the interquartile range and the median). This relationship implies an increase in the probability mass associated with low levels of growth. This result can be interpreted as an increase in the negative bias of growth expectations in the face of greater uncertainty. It should be noted that, in this regard, other analyses have found similar results for other economies such as the US and China (see Gu et al. (2021) and Jovanovic and Ma (2020)).

Figure 10: Median and Interquartile Range Scatterplot of Quantile Regression



(a) Three months ahead (b) Twelve months ahead

Source: Own elaboration.

Notes: based on the Benchmark Model, we estimate fitted values $\hat{y}^{0.25}_{t+h}$, $\hat{y}^{0.50}_{t+h}$ and $\hat{y}^{0.75}_{t+h}$ for each period t in the sample and forecast horizon h. Interquartile range (IQR) for period t and forecast horizon h is defined as $\hat{y}^{0.75}_{t+h} - \hat{y}^{0.25}_{t+h}$. Meanwhile, the median (q50) for period t and forecast horizon h is $\hat{y}^{0.50}_{t+h}$. Figures present the time series' scatterplot of IQR and q50 corresponding to the forecast horizons $h = 3$ (left) and $h = 12$ (right).

Another way to analyze the effect of uncertainty on the distribution of IGAE growth is through the comparison of adjusted $skewed - t$ distribution functions. For example, through these estimates it is possible to determine the cumulative distribution functions and compare the probability mass associated with different levels of growth for conditional and unconditional adjusted distributions at the level of uncertainty in the economy. Figure 11 shows the estimated values of $\hat{Q}_{y_{t+h}|x_t}(\tau \mid x_t)$ conditional on observed IGAE, inflation, IPUS and MUI (Quantile Regression), and two versions of estimations of the cumulative $skewed-t$ distribution. The first one is conditional on observed IGAE, inflation and IPUS ($skewed-t$ Without MUI), and the other one conditional on the previous regressors plus the MUI ($skewed - t$

[22]A simple measure of dispersion that can be analyzed from the estimates of the quantile regressions, which is defined as the difference or distance between the first and third quartiles of a distribution.

With MUI) for four periods of the sample and a forecast horizon of three months. Through these estimates, it is possible to compare the effect of uncertainty on growth expectations during two relatively different periods in the level of uncertainty in the economy.[23] In particular, during the months of April and May of 2015 the economy showed relatively low levels of uncertainty, whereas the months of April and May 2020 registered the highest, associated with the effects of COVID-19 Pandemic.

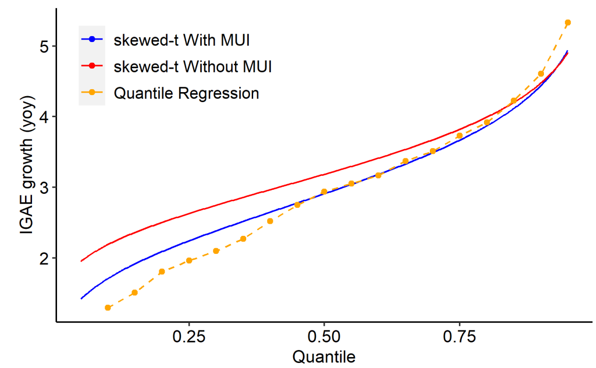
Figure 11 shows that, during the period of relatively low uncertainty, the distribution $skewed-t$ *With MUI* does not deviate significantly from the distribution $skewed-t$ *Without MUI* . In particular, during the period of April 2015, a certain negative bias of growth expectations is observed, while, in the case of the period of May 2015, the estimates of the distributions suggest a slight upward bias of growth expectations. In contrast, during the months of April and May 2020, a significant difference is observed between the distributions $skewed-t$ *With MUI* and $skewed-t$ *Without MUI*, that suggests a significant shift to the left of the expected output growth distribution, which can be interpreted as an increase in the negative bias of growth expectations during that period.

These results would seem to suggest that our estimates are especially sensitive to the presence of recessive periods in the sample. In order to assess the robustness of our results, we estimate equation 7 for a restricted sample that covers the period from January 1997 to September 2008, period that does not include IGAE falls associated with the Mexican Peso Crisis of 1994, the Great Financial Crisis of 2008 and the recent COVID-19 Pandemic. Table 2 shows the estimates of the Benchmark Model for that sub-sample. The results suggest that our model is robust to the exclusion of periods with deep drops in economic activity, since a negative and statistically significant effect of the MUI remains on the left tail of the growth distribution. However, it is clear that the exclusion of crisis periods from the sample has an important effect on the magnitude of marginal effects associated with MUI, which, in general, are lower in absolute value than those obtained for the complete sample. Indeed, for the tenth quantile and the median, we estimate and effect of -0.20 and -0.12 for the restricted sample, that contrast with an effect of -0.50 and -0.27 for the unrestricted sample. This way, the previous evidence shows that the MUI is useful to identify the negative bias of the expected growth in Mexico even in periods of relative stability.

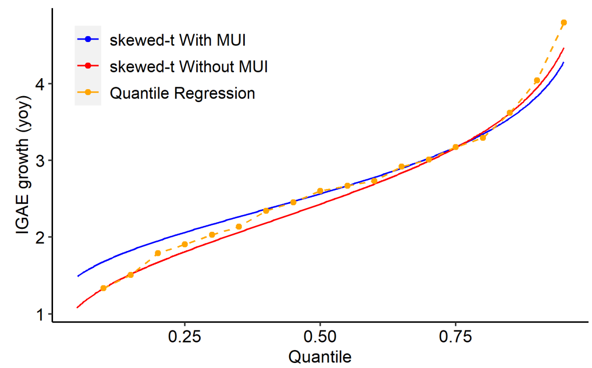
Our results are similar to those obtained by Jovanovic and Ma (2020) and Gu et al. (2021) for the cases of the US and China, respectively. Jovanovic and Ma (2020) propose a theoretical model in which growth and uncertainty in the economy are determined endogenously. Their results suggest that the rapid adoption of new technologies increases economic uncertainty and can cause productivity to decline. Through this mechanism, the equilibrium growth

[23] According to the trajectory of the MUI, during April and May 2015, relatively low levels of uncertainty were observed in Mexico after an increase associated with the drop in international prices for Mexican oil. Subsequently, although the MUI remained at relatively low levels between 2015 and 2018 compared to other periods of high uncertainty, it exhibited a slight upward trend associated with various national and international episodes such as the electoral processes in Mexico and the US, and the renegotiation of the North American Free Trade Agreement (NAFTA). However, during this period, relatively stable economic growth levels were maintained. In particular, the annual growth rate of IGAE between 2015 and 2018 was around 2%. In contrast, during April and May 2020, the highest levels of macroeconomic uncertainty in the Mexican economy were observed since 1993 associated with the shocks of COVID-19 Pandemic. During that period and subsequent months, the level of uncertainty in Mexico has been at relatively high levels despite the gradual recovery of economic activity that has been observed since the second half of 2020.

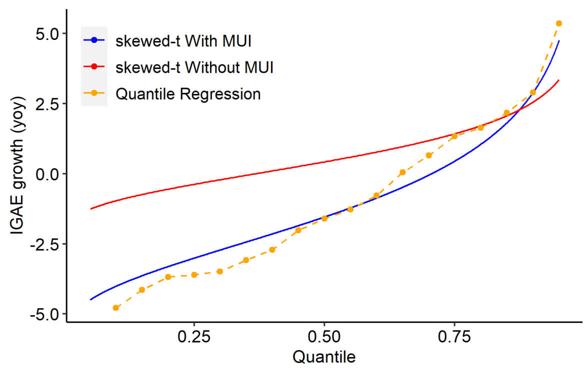
Figure 11: Quantile Regression and the $skewed - t$ Distribution (h = three months)



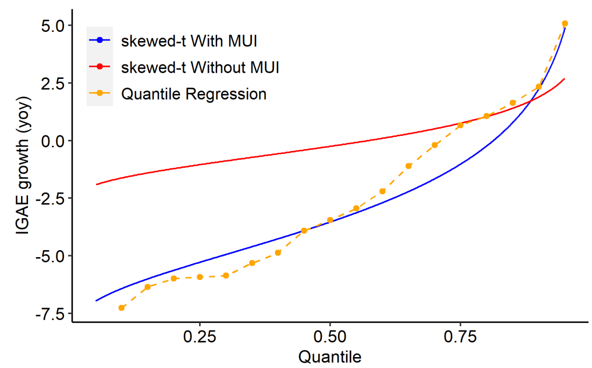
(a) April 2015



(b) May 2015



(c) April 2020



(d) May 2020

Source: Own elaboration.

distribution is negatively skewed: greater uncertainty leads to a reallocation of labor across activities, and increases the probability mass associated with low growth levels. To empirically contrast some of their results, Jovanovic and Ma (2020) perform a GaR-type analysis in which they show that greater uncertainty is associated with a more dispersed distribution of production growth, presenting a negative impact on the lower tail of the distribution of growth, while exhibiting a much smaller and not significant, impact on its upper tail. Gu et al. (2021) analyzes the impact of the Economic Policy Uncertainty Index (EPU) on the distribution of China's GDP growth through the GaR methodology of Adrian et al. (2019). Similar to our results, the authors find that the entire forecast distribution of GDP growth conditional on the EPU index exhibits substantial fluctuations over time. They conclude that the inclusion of the EPU alters the peaks of the forecast distribution, and amplifies the risk in the left tail of growth distribution.

3.4 Relative Probability Gain and Entropy

In the previous section we presented evidence for the fact that, given a considerable increase in the level of uncertainty, the distribution $skewed - t$ *with MUI* associates a greater probability mass to low growth levels than the distribution $skewed - t$ *without MUI*, for a forecast

Table 2: Estimated Coefficients of Benchmark Model (h = 3 months; Jan-97 to Sep-08)

	10th Quantile			25th Quantile		
	Coef.	Lower	Upper	Coef.	Lower	Upper
Intercept	13.20 **	2.8	23.6	14.64 ***	5.8	23.5
IGAE	0.19	-0.1	0.4	0.39 ***	0.2	0.6
MUI	-0.20 **	-0.3	0.0	-0.21 ***	-0.3	-0.1
IPUS	0.37 ***	0.2	0.5	0.27 ***	0.1	0.4
Inflation	0.09	0.0	0.2	0.11 **	0.0	0.2

	50th Quantile			90th Quantile		
	Coef.	Lower	Upper	Coef.	Lower	Upper
Intercept	8.58 *	0.7	16.4	6.18	-11.4	23.8
IGAE	0.57 ***	0.4	0.7	0.58 ***	0.4	0.8
MUI	-0.12 *	-0.2	0.0	-0.06	-0.3	0.2
IPUS	0.23 ***	0.1	0.3	0.22	0.0	0.5
Inflation	0.06	0.0	0.1	0.03	-0.1	0.1

Source: Own elaboration.
Notes "***", "**", "*" if $p < 0.01$, $p < 0.05$, and $p < 0.1$, respectively. Lower and Upper indicate the 90% confidence interval built by bootstrap.

horizon of three months.[24] In this sense, it can be interpreted that by conditioning the distribution of the expected growth of activity in the MUI, a relative probability gain (GRP) is obtained to predict low growth levels in the face of increases in uncertainty. Given the above argument, for each sample period t, and a given reference growth level g_t, the GRP is defined as the difference between the cumulative $skewed-t$ probability distributions conditional and unconditional in the MUI, evaluated at g_t. Formally, we calculate the GRP as follows:

$$GRP_t^h(g_t) = F_{IGAE}^h(g_t; X_{t-h}, MUI_{t-h}) - G_{IGAE}^h(g_t; X_{t-h}) \tag{8}$$

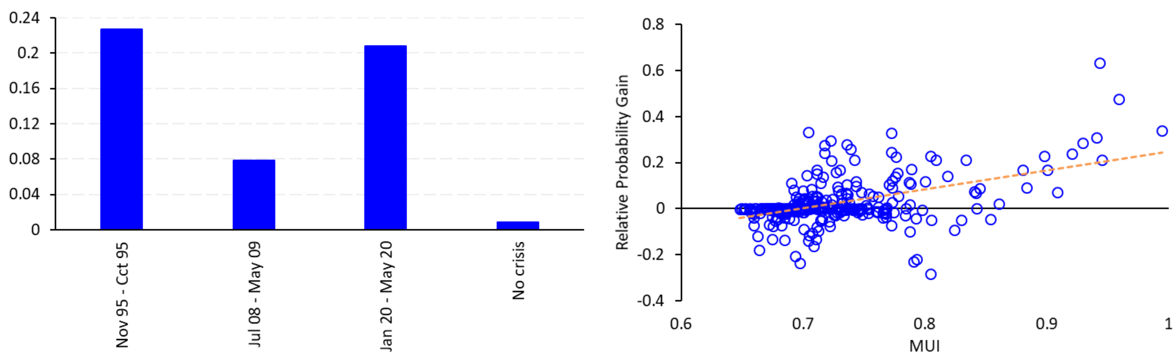
Where $GRP_t^h(g_t)$ is the GRP in period t for a forecast horizon h and a reference growth level of g_t, $F_{IGAE}^h(y_t; X_{t-h}, MUI_{t-h})$ is the cumulative distribution $skewed-t$ *with MUI* evaluated at g_t and $G_{IGAE}^h(y_t; X_{t-h})$ is the cumulative distribution $skewed-t$ *without MUI* evaluated at g_t. X_{t-h} is a set of explanatory variables of economic conditions observed in the period $t-h$ (IGAE, IPUS and inflation).

Although the GRP can be calculated for any reference growth level g_t, it has been argued that the MUI helps to identify the negative bias of growth expectations, especially during periods where abrupt falls in output are observed. In this sense, we carry out an exercise in which we calculate the average GRP of having negative growth (i.e. $g_t = 0$) for the periods of the 1994 and 2008 crises and the COVID-19 Pandemic. In particular, for each of the economic crises, we calculated the average GRP for those periods in which a sustained fall in the IGAE was observed until reaching the maximum fall corresponding to the crisis period. Figure 12 presents the results of this exercise. The estimates suggest a significant GRP for the

[24]It should be noted that similar results are observed for forecast horizons of one, six and twelve months.

three crisis periods analyzed, and no significant GRP is observed for the period with no crisis. In addition to the above, the strong positive correlation that we found between the GRP and the MUI stands out. Intuitively, given that the MUI contributes significantly to identifying the negative bias of growth expectations, it is reasonable to obtain a higher GRP in the face of higher levels of uncertainty in the economy.

Figure 12: Relative Probability Gain and MUI



(a) Relative Probability Gain

(b) MUI vs. Relative Probability Gain

Source: Own elaboration.
Notes: The first three periods plotted on (a) represent the Mexican Peso Crisis, the Great Financial Crisis, and the COVID-19 Pandemic. No crisis refers to the rest of the sample, as a whole. The value for each bar of (a) represents the average GRP in the period.

A complementary and related measure to the GRP to analyze the risk of growth expectations is the relative entropy. According to Adrian et al. (2019), the upside and downside vulnerability of expected growth can be quantified as the "extra" probability mass that the conditional density in the MUI assigns to the left and right tail outcomes of the distribution, in relation to the probability of these results under the unconditional density. By comparing the probability assigned to the extreme results by the conditional density in the MUI with the probability assigned to the same results by the unconditional density, we evaluate whether the distribution of expected growth in a given period implies a greater vulnerability around the modal forecast. Thus, when the upper relative entropy (URE) is high, the conditional density assigns a higher probability to right tail growth outcomes than the unconditional density. Conversely, when the lower relative entropy (LRE) is high, the conditional density assigns a higher probability to left tail growth outcomes than the unconditional density. Formally, the lower $E^{I}_{t,h}$ and the upper $E^{S}_{t,h}$ relative entropies in period t for estimates with forecast horizon h are define as:

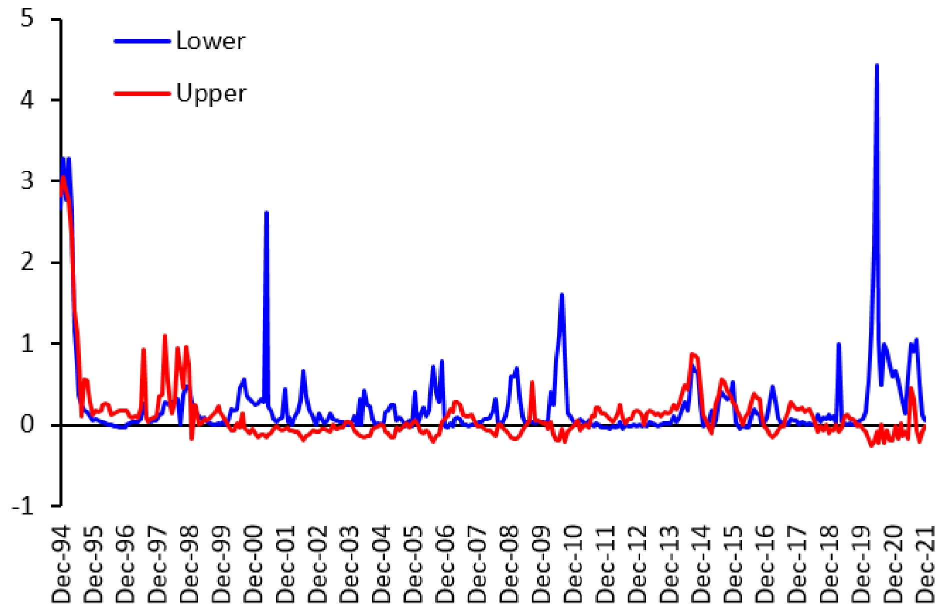
$$E^{I}_{t,h} = -\int_{-\infty}^{\hat{F}_h^{-1}(0.5|x_t,MUI_t)} log\left(\frac{\hat{g}_h\left(y \mid x_t\right)}{\hat{f}_h\left(y \mid x_t, MUI_t\right)}\right)\hat{f}_h\left(y \mid x_t, MUI_t\right)dy \qquad (9)$$

$$E^{S}_{t,h} = -\int_{\hat{F}_h^{-1}(0.5|x_t,MUI_t)}^{\infty} log\left(\frac{\hat{g}_h\left(y \mid x_t\right)}{\hat{f}_h\left(y \mid x_t, MUI_t\right)}\right)\hat{f}_h\left(y \mid x_t, MUI_t\right)dy \qquad (10)$$

Where, $\hat{g}_h\left(y \mid x_t\right)$ is the adjusted density function $skewed{-}t$ *without MUI*; $\hat{f}_h\left(y \mid x_t, MUI_t\right)$

is the adjusted density $skewed\!-\!t$ *with MUI*; and $\hat{F}_h^{-1}(0.5 \mid x_t, MUI_t)$ is the median of function $\hat{f}_h(y \mid x_t, MUI_t)$.

Figure 13: Relative Entropy Index



Source: Own elaboration.

Consistent with our calculations (see Figure 13), this measure of expected growth vulnerability shows that there were considerable downside risks to growth both during the Mexican Peso Crisis of 1994 and the COVID-19 Pandemic. Downside risks seems to be relatively more persistent during the COVID-19 Pandemic.[25] Our estimates did not detect significantly high downside risks during the period of the Great Financial Crisis of 2008. Intuitively, these differences can be derived from the relative importance of the origin of uncertainty. While vulnerabilities associated with the Mexican Peso Crisis of 1994 were deeper and more structural for Mexico, those of the Great Financial Crisis of 2008 were due mainly to external shocks and encountered a relatively strengthened Mexican economy, both in its macroeconomic fundamentals and in relation to financial regulation standards that could have helped the financial shocks during this period to have a more limited impact on the real economy.

3.5 Robustness Analysis

The previous results show significant evidence of the impact of uncertainty on the distribution of expected IGAE growth in Mexico. However, it is possible that our measure of uncertainty

[25]Upper relative entropy estimates show relatively high levels during the Mexican Peso Crisis of 1994 period. This result is derived from the particular shape of the adjusted $skewed-t$ distribution functions for that period. In particular, the estimates of the $skewed\!-\!t$ *without MUI* functions are characterized by a leptokurtic shape with a relatively small dispersion, while the $t-$*biased with MUI* functions have a significantly bigger dispersion and a platykurtic form. In this way, the upper relative entropy shows high levels because the distribution $skewed-t$ *with MUI* presents a relatively higher probability than the $skewed-t$ *without MUI* for positive extreme values of growth, due to the high dispersion of conditional distribution in MUI.

(MUI) is acting as a proxy variable for other determinants of the distribution of expected growth for economic activity, such as financial conditions or sources of uncertainty that are not fully captured by MUI, and have been omitted from the analysis. In this sense, we carry out a series of robustness exercises that allow us to establish the validity of our results in the face of other relevant indicators that could be strongly related to the MUI.

For instance, there is some evidence in the case of Mexico that financial conditions could impact the performance of economic activity. In general, financial conditions indices have proven to be useful tools for analyzing the performance of the economy in the presence of events that trigger widespread uncertainty about economic expectations. In particular, Carrillo and García (2021) construct an FCI and find evidence that real variables in the Mexican economy such as GDP, consumption, and investment respond negatively and significantly to negative shocks of financial conditions. Additionally, there is also some evidence that financial conditions seem to have a significant impact on the distribution of expected growth in Mexico (Banxico (2019, 2020a)).[26]

To control our estimates for the state of financial conditions, we include the FCI in our Benchmark Model. In particular, we estimate the following quantile regression:

$$y_{t+h}^{\tau} = \alpha_{\tau} + \beta_{\tau} y_t + \delta_{\tau} INF_t + \gamma_{\tau} IPUS_t + \theta_{\tau} FCI_t + \rho_{\tau} MUI_t + \varepsilon_t^{\tau} \tag{11}$$

Estimates of equation 11 show that once we control for uncertainty through the MUI, the FCI do not present a statistically significant effect on the distribution of expected IGAE growth. In contrast, estimated coefficients of equation 11 associated with the MUI continue to be negative and statistically significant for the left part of the distribution, with their marginal effects being similar to those obtained in the original estimation of the Benchmark Model (see Table 3). These results, together with the analysis of the relationship between uncertainty and growth through a VAR model presented in previous sections, show that macroeconomic uncertainty is an important determinant of economic growth in Mexico, even controlling for the state of financial conditions and other determinants of growth.

The previous result stands out due to the contrast with Adrian et al. (2019) for the case of the US and Banxico (2019, 2020a) for the case of Mexico. Intuitively, it is possible that in the case of economies such as Mexico, relevant information to analyze the distribution of expected growth that would be contained in indicators such as the FCI, could be already included in other indicators whose purpose is to measure the level of uncertainty in the country such as the MUI. This, in turn, could be associated with characteristics of the Mexican economy such as a greater exposure to risk and a greater volatility of the financial system compared to that of developed countries.

In addition, we evaluate the validity of our results including other indicators closely related to the financial system, and other measures of uncertainty both at the national and international levels (see Appendix B). Specifically, we include in our estimates indicators such as the US NFCI as a measure of the state of financial conditions not only in the US but regionally, as well as the EPU for Mexico, for the US and at a global level in order to have measures

[26]In the Appendix D We present an exercise in which we estimate a GaR model for Mexico based on the original methodology of Adrian et al. (2019), using the FCI of Carrillo and García (2021) without controlling for uncertainty (MUI). This exercise shows that, indeed, financial conditions seem to have a significant impact on the distribution of the expected growth in Mexico.

Table 3: Estimated Coefficients of Benchmark Model with FCI (h = 3 months)

	10th Quantile			25th Quantile		
	Coef.	Lower	Upper	Coef.	Lower	Upper
Intercept	37.48 ***	26.0	48.9	29.09 ***	23.4	34.8
Inflation	0.18 ***	0.1	0.3	0.20 ***	0.1	0.3
IPUS	0.17 ***	0.1	0.3	0.09 **	0.0	0.2
MUI	-0.56 ***	-0.7	-0.4	-0.43 ***	-0.5	-0.3
IGAE	0.33 **	0.1	0.5	0.43 ***	0.3	0.6
FCI	0.01	0.0	0.0	0.00	0.0	0.0

	50th Quantile			90th Quantile		
	Coef.	Lower	Upper	Coef.	Lower	Upper
Intercept	17.70 ***	7.8	27.6	-1.21	-7.3	4.8
Inflation	0.17 ***	0.1	0.2	0.10 ***	0.1	0.1
IPUS	0.03	-0.1	0.1	-0.03	-0.2	0.1
MUI	-0.25 ***	-0.4	-0.1	0.05	0.0	0.1
IGAE	0.59 ***	0.4	0.7	0.53 ***	0.4	0.7
FCI	0.00	0.0	0.0	-0.01	0.0	0.0

Source: Own elaboration.
Notes "***", "**", "*" if $p < 0.01$, $p < 0.05$, and $p < 0.1$, respectively. Lower and Upper indicate the 90% confidence interval built by bootstrap.

of economic policy uncertainty both domestically, as well as regionally and globally. Our results show that the inclusion of these indicators in the estimates of our Benchmark Model do not significantly affect our results about the impact of the MUI on the distribution of expected economic growth in Mexico. These results contrast with those of Gu et al. (2021), because the EPU of Mexico does not turn out to be statistically significant once the MUI is including in estimations.

Additionally, we carried out other exercises with other more traditional indicators to measure the uncertainty and the level of risk prevailing in Mexico, such as the nominal (and real) exchange rate[27] and the risk premium defined as the difference between the funds rate US federal funds and the CETES rate in Mexico. Similarly to the previous cases, our results were robust to the inclusion of these indicators (see Appendix B). However, it should be noted that a depreciation (nominal and real) of the exchange rate has a negative and statistically significant effect on the left tail of the distribution of the expected IGAE growth. This result suggests that both the MUI and exchange rate depreciation could be complementary to analyze the negative bias of economic growth projections in Mexico.

[27]The Benchmark Model includes annual percentage growth rates for both nominal and real exchange rate, in order to assess the impact of an annual depreciation/appreciation of exchange rate on expected growth.

3.6 Analysis of the Impact of the MUI with Alternative Measures of Economic Activity

As an additional robustness exercise, we present a second set of estimates in which, instead of IGAE we consider alternative indicators of economic activity. On the demand side, we include private consumption and gross fixed investment. On the supply side, we consider industrial production and tertiary activities. Finally, as a measure of activity on the labor market side, we use the level of formal employment and the employment rate (see Appendix B).[28] Our results show that the effect of uncertainty on the distribution of expected growth is robust to the use of the aforementioned alternative measures of economic activity. These results hold for horizons of one, three, six and twelve months, as in the case of IGAE.

It is worth highlighting the analysis of gross fixed investment because, unlike the rest of the components of aggregate demand, other indicators on the supply side, and the labor market, it presents greater volatility and dependence on uncertainty. This is because uncertainty affects expectations about the future performance of the economy and, therefore, directly affects the expected returns on investment. In particular, our estimates suggest that annual investment growth is much more sensitive to changes in the level of uncertainty. The estimated coefficients of our model suggest a marginal effect of the MUI on investment growth of -1.16 pp for the tenth quantile, while for the rest of the alternative measures of economic activity, including the IGAE, the same marginal effect is between -0.08 and -0.64 pp.

Finally, we also carried out an exercise with quarterly frequency data using Mexico's GDP as a measure of economic activity. It is possible that by smoothing the series through a quarterly mean, and thereby registering increases in the MUI of lesser magnitude, the impact of uncertainty will have a lower incidence on the expected economic activity. In this way, through this exercise we seek to evaluate the robustness of our results in the face of lower frequency data.

The results of this exercise are similar to those obtained for IGAE and show that the validity of our estimates does not depend on the presence of significantly high increases in the MUI in its original monthly frequency (see Appendix C). In particular, it is found that increases in uncertainty are not only associated with increases in the dispersion of the distribution of expected GDP growth, but also with a shift of said distribution to the left, contributing to identify the negative bias of expected growth in Mexico.[29]

[28] All alternative indicators of economic activity are included in the Benchmark Model as annual percentage growth rates with the exception of employment rate that was included in annual variation.

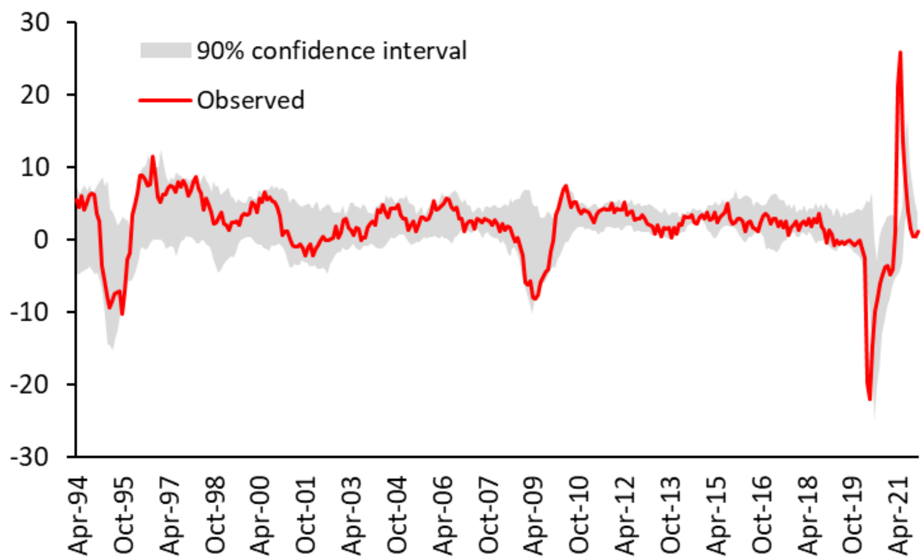
[29] It should be noted that these results help to reject the fact that, since IGAE is an input to build the MUI, the relationship between the MUI and economic activity measured through the IGAE is derived from a endogeneity problem. On the one hand, as mentioned above, the IGAE is only one of the 125 monthly series used to build the MUI. Second, although the quarterly IGAE and the GDP are strongly correlated, in general, different methodologies are used to construct these measures of economic activity.

4 Analysis of Uncertainty during Great Economic Crises in Mexico

In this section we present a brief analysis of uncertainty and its effects on growth during the periods of the most significant crises in the sample: the Mexican Peso Crisis of 1994, the Great Financial Crisis of 2008 and the COVID-19 Pandemic. These periods have been characterized by deep falls in economic activity and are of special interest for our analysis due to two particular reasons. First, the estimates of our model seem to be especially relevant for the analysis of recessions because they allow us to identify the impact of uncertainty on the negative bias of growth expectations. Second, although the causes of these crises are completely different from each other, they have in common that these periods were characterized by high levels of uncertainty.

Indeed, as mentioned above, MUI estimates identify periods of crisis as those in which the highest levels of uncertainty have been observed (see figure 2). Furthermore, our estimates suggest that, during periods of deep recessions, the observed growth of economic activity is more similar to estimates of the lower quantiles of the growth distribution. In other words, output falls are accompanied by high levels of uncertainty that exacerbate the negative bias of growth projections. This characteristic makes the central moments of the estimated distribution relatively optimistic with respect to the actually observed values (Figure 14).

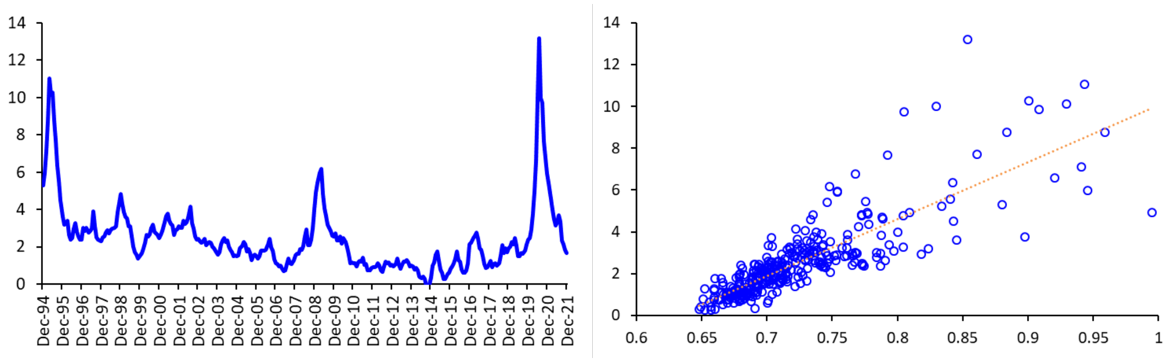
Figure 14: IGAE (yoy) growth Estimated Conditional Distribution



Source: Own elaboration.
Notes: Confidence Interval's upper and lower bound refer to the quantile regression's fitted values $\hat{Q}_{t+3}$ for quantiles 95 and 5, respectively.

Our results also imply that estimates of the distribution of expected economic growth during recessions are accompanied by greater dispersion. Figure 15 shows the dispersion of the expected distribution of IGAE growth, for a forecast horizon of three months, measured through the interquartile range. Indeed, in mid-2020 a historical maximum of this dispersion measure was reached as a reflection of the effects of the COVID-19 Pandemic. The second event with the greatest dispersion occurs during the Mexican Peso Crisis of 1994, followed by the Great Financial Crisis of 2008. This greater degree of dispersion of the distribution of expected growth can be associated with the presence of higher levels of uncertainty. In particular, when comparing this measure of dispersion of growth expectations with the MUI, a strong positive correlation is found between both indicators. In this way, as mentioned above, our results not only suggest that increases in uncertainty lead to an increase in dispersion of expected growth distribution, but also to a shift to the left, that implies an increase of the probability of observing especially lower and negative growth levels in the case of recessive periods.

Figure 15: IGAE (yoy) growth Distribution and MUI



(a) Interquantile Range (b) MUI vs. Interquantile Range

Source: Own elaboration.

In the rest of the section we present the estimates of the density and cumulative probability functions for periods that we consider to be representative of these crises, in order to observe the effect of uncertainty on these estimates, and have a more comprehensive picture of the negative bias of growth expectations that prevailed in those periods. [30]

4.1 Mexican Peso Crisis of 1994

The Mexican Peso Crisis of 1994 was characterized by an environment of high uncertainty associated with various macroeconomic vulnerabilities that lead to a drastic and unfavorable change in expectations regarding the performance of the Mexican economy. In addition, the level of uncertainty was exacerbated by inadequate management of the currency devaluation that triggered a massive capital outflow. This event resulted in a change in the exchange rate regime and a severe economic recession.

Indeed, consistent with the environment in which the Mexican Peso Crisis of 1994 took place, the MUI shows a significant increase since mid-1994, reaching maximum levels between December 1994 and March 1995. In this context, our estimates of the distribution of expected growth show a significant impact of uncertainty. In particular, for April, May and

[30]For more details on the main causes and evolution of the 1994 and 2008 crises, see the historical account of CEEY (2010), de la Luz Juárez et al. (2015), Ortiz (2009a, 2009b), and Perojo (2018).

June 1995, months in which the deepest drops in the output occurred. In both the quantile regressions and in the $skewed - t$ distributions, a significant increase in the dispersion of the distribution is observed, and a significant shift of the density function to the left, as well as a significant average GRP of having an economic crisis during that period (see Figure 12).

More specifically, in May 1995, the $skewed - t$ *with MUI* distribution shows a significant bias towards negative levels of IGAE growth. In contrast, the $skewed - t$ *without MUI* distribution was still consistent with the expectation of positive growth. Likewise, the estimates of the cumulative distributions for the same period show a substantial increase in the probability mass associated with negative growth. Indeed, the GRP of observing negative growth in that period is 0.6 pp according to our estimates (see Figure 16).[31] All these results point to the presence of a significant negative bias in growth expectations during the Mexican Peso Crisis of 1994. This result is consistent with the entropy estimates presented above (see Figure 13).

4.2 Great Financial Crisis of 2008

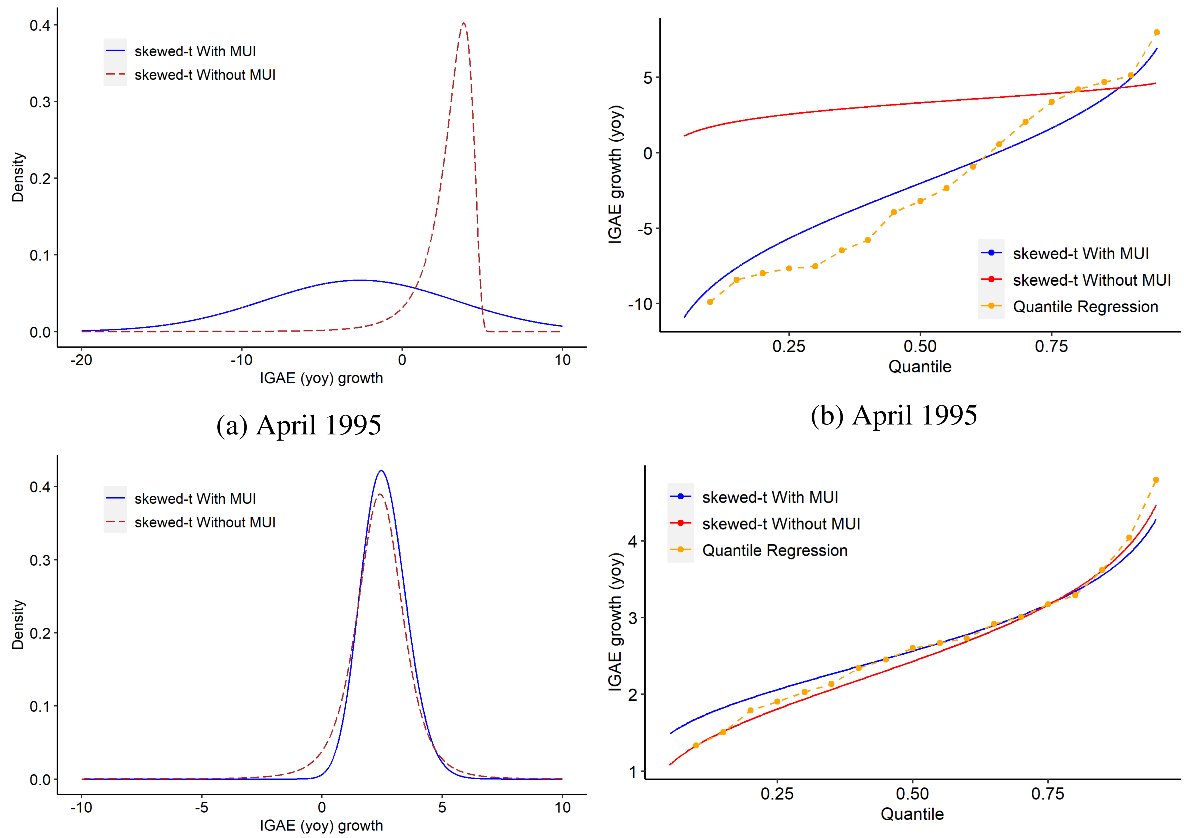
Unlike the financial crises in emerging countries associated with macroeconomic imbalances and other economic, regulatory and financial vulnerabilities, the Great Financial Crisis of 2008 differed from its predecessors due to characteristics such as its global nature, magnitude and simultaneity in various economies. Since the end of 2008, the crisis spread rapidly outside the US, first to other industrialized countries, and later to emerging economies through two main shocks: one in demand and the other in finance. In this sense, a strong contraction in the demand for exports was observed, as well as an increase in the risk positions of emerging countries. The foregoing, together with an increase in risk aversion and a contraction in liquidity, contributed to a significant increase in the level of uncertainty in Mexico and in the rest of the world, accompanied by a deep recession at the global level. In particular, Mexico's GDP fell nearly 8% during the second quarter of 2009.

Our estimates of the distribution of expected growth for the month of May 2009 suggest a certain negative bias in expectations, while the $skewed - t$ *with MUI* distribution shows a slight shift to the left and a greater dispersion than the estimation of the $skewed - t$ *without MUI* distribution (see Figure 17). In this sense, as previously shown, our estimates also present a significant increase in the dispersion of growth expectations (see Figure 15) and a GRP increase during the crisis period (see Figure 12). However, unlike the analysis of the Mexican Peso Crisis of 1994, this negative growth bias appears to be of less magnitude. In particular, both the conditional and the unconditional distribution in MUI, are compatible with the expectation of negative growth of considerable magnitude, which implies a relatively small GRP.

The difference between estimates of distributions, with those calculated for the Mexican Peso Crisis of 1994, could be due to the nature of uncertainty and shocks that caused the fall in output. While in 1994-1995 the crisis originated in strong internal imbalances, an the implementation of policies that lead to an exacerbation of the initial shock, significantly

[31] The estimates corresponding to May and June 1995, which have been omitted for the sake of parsimony, present similar results, although it can be noted that despite the fact both approximations of the quantile regressions and the $skewed - t$ distributions (with and without MUI) are consistent with the higher expectation of observing negative growth, the conditional estimates in the MUI assign a higher probability to having much lower growth rates.

Figure 16: Probability Density Function and Cumulative Distribution Function



(a) April 1995

(b) April 1995

(c) May 2015

(d) May 2015

Source: Own elaboration.
Notes: Distributions are estimated from the models with 3 month forecast horizon. Cumulative density function plots (b and d) have the quantile on the x-axis, therefore it should be interpreted as the probability of having a y-o-y growth less than or equal to the value on the y-axis.

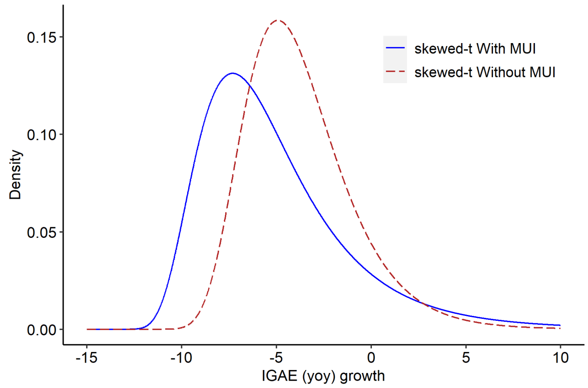
raising uncertainty, for the Great Financial Crisis of 2008 the initial shock was observed since September 2008 in the US and spread rapidly to advanced economies with a greater lag to emerging economies. In this sense, the repercussions of the crisis on economic activity in Mexico came, mainly, from the weakness of financial markets and foreign demand, in such a way that uncertainty was fueled by the growing risk aversion associated with global factors.

4.3 COVID-19 Pandemic

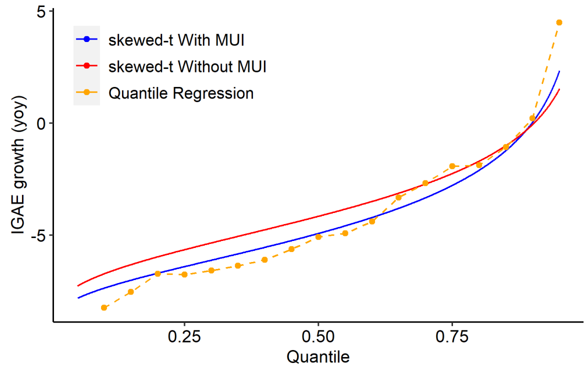
The economic crisis associated with the COVID-19 Pandemic has profoundly impacted the global economy, originating from a health emergency and not from an economic phenomenon in itself. However, similar to the 2008 Financial Crisis, it has had a global reach that has profoundly affected growth, employment and the financial systems of virtually every country in the world.

In Mexico, in the beginning of 2020, in response to the COVID-19 health crisis, au-

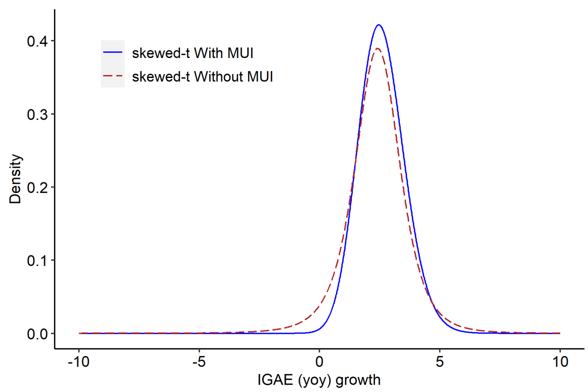
Figure 17: Probability Density Function and Cumulative Distribution Function



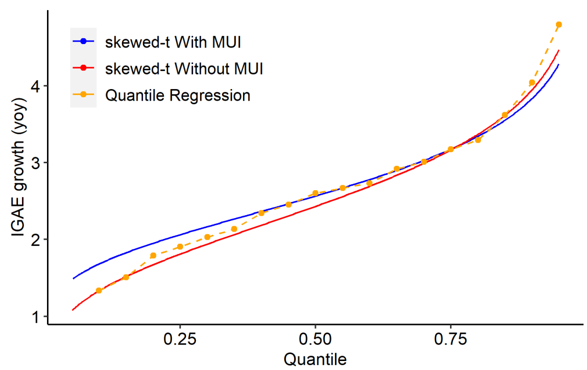
(a) May 2009



(b) May 2009



(c) May 2015



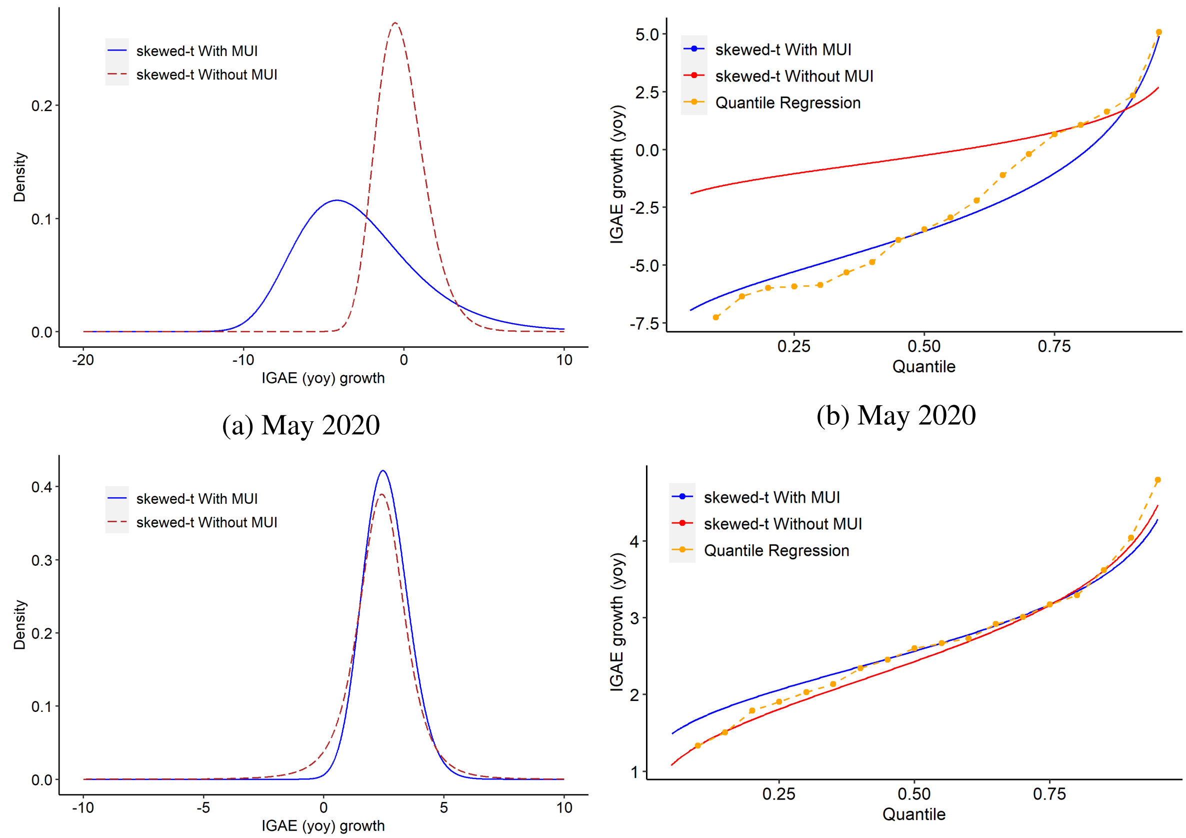
(d) May 2015

Own elaboration.
Notes: Distributions are estimated from the models with 3 month forecast horizon. Cumulative density function plots (b and d) have the quantile on the x-axis, therefore it should be interpreted as the probability of having a y-o-y growth less than or equal to the value on the y-axis.

thorities implemented social distancing measures and the closure of non-essential activities, emulating the responses taken in other countries. We know that these actions translated into shocks to the economy both on the demand and on the supply side. Likewise, as Mexico is an open economy and integrated into global value chains, there have been effects due to a lower demand for Mexican exports, as well as interruptions in the supply chains that have affected the supply of certain inputs (mainly at the beginning of the pandemic due to the measures implemented to contain contagion in Asian economies, especially China, and more recently with the shortage of semiconductors that has severely affected the automotive industry).

The estimated probability distributions of expected growth for the month of May 2020, period in which the greatest historical drop in economic activity was recorded and also the greatest increase in uncertainty registered through the MUI (see Figure 18), show similarly to the cases of the Mexican Peso Crisis of 1994 and the Great Financial Crisis of 2008, an increase in the negative bias of growth expectations (see Figure 12). Likewise, our estimates of relative entropy show a very important increase in the vulnerability of growth, of greater

Figure 18: Probability Density Function and Cumulative Distribution Function



(a) May 2020

(b) May 2020

(c) May 2015

(d) May 2015

Own elaboration.
Notes: Distributions are estimated from the models with 3 month forecast horizon. Cumulative density function plots (b and d) have the quantile on the x-axis, therefore it should be interpreted as the probability of having a y-o-y growth less than or equal to the value on the y-axis.

magnitude than those registered during previous crises, which has decreased significantly in the last periods of the sample (see Figure 13). However, unlike the estimates for the periods of the Mexican Peso Crisis of 1994 and the 2008 crisis, where observed growth levels were located within the 10th and 90th quantiles of the estimated distribution, in the case of the COVID Pandemic -19 the observed growth rate of -21.6% in the month of May 2020 is well outside this range (see Figure 14).[32] The foregoing is evidence that the period of the pandemic has been characterized by registering very atypical growth levels that highlight the difficulty to measure its impact on economic activity.

In this regard, we consider necessary to justify, to a certain extent, the reasons why we observe a relatively important error in the adjustment of estimates of the distribution of expected growth during the period of the COVID-19 Pandemic. In the first place, unlike previous recessive periods, this economic crisis had its origin, mainly, in non-economic factors

[32]It should be noted that this characteristic of observed level of annual IGAE growth is maintained even considering confidence bands at 99% for estimations of the distribution

associated with the health emergency. This characteristic makes it difficult for policymakers to estimate the incidence of each of the shocks, and could generate greater uncertainty associated with the lack of adequate policy responses to counteract the crisis. Second, although the pandemic has had general repercussions at a global level, and across all sectors of activity, its evolution has not been simultaneous and the magnitude of its effects has been heterogeneous both across countries and sectors of activity. This has impacted, for example, the continuity of supply chains, especially inputs for the manufacturing industry. Finally, the evolution of the COVID-19 Pandemic and the possibility of sustaining with some certainty the opening of economic activities has depended, to a large extent, on the development, production and distribution of effective vaccines against the virus. More recently, this evolution has not only depended on the progress of vaccination campaigns, but also on the emergence of new variants of the virus that are potentially more contagious.[33] Due to the above, it is not only reasonable that any estimate of the evolution of economic activity during the pandemic is subject to measurement errors that were difficult to face in previous situations, but also that any estimate of the degree of uncertainty prevailing during the pandemic will be subject to a problem of underestimation that, finally, would also lead to underestimating its effects on the economy.

5 Conclusions

The analysis of the relationship between the level of uncertainty and growth expectations is of interest from both a theoretical and empirical point of view, as well as for economic policy analysis. In particular, it is important for policymakers to understand the channels through which uncertainty impacts the real economy, since high uncertainty is one of the main characteristics of recessions, and can pose an obstacle to recovery as it affects consumption and investment decisions, among other things. This topic is of special interest in the current situation of the COVID-19 Pandemic, which has generated a high degree of uncertainty about its evolution and its possible long-term consequences on economic activity both globally and for individual countries.

In this sense, in this paper we analyze the empirical relationship between uncertainty and growth expectations in Mexico. In a first approximation, we analyze the impact of uncertainty on growth through the estimates of an Autoregressive Vector (VAR) of IGAE annual growth rate, controlling for the MUI and other determinants of economic activity such as the rate of US federal funds, exchange rate, consumption and investment, CETES rate, and financial conditions measured through the FCI proposed by Carrillo and García (2021). We showed that uncertainty has a negative and statistically significant impact on economic growth, consumption and investment in Mexico. In turn, it highlights that increases in the level of uncertainty lead to tighter financial conditions, while, in contrast, a shock in financial conditions does not have an effect that is statistically different from zero on activity, consumption and investment.

[33] Although our sample covers until December 2021, and variants of the coronavirus such as Omicron began to appear, in Mexico, since January 2022, the impact of the surge of variants on the evolution of the pandemic is evident. For example, as of August 2021, more than 90% of the new cases of COVID-19 belonged to the Delta variant of the virus (Badillo (2021)).

Although above results show evidence that uncertainty is an important determinant of growth, according to Adrian et al. (2019), point forecast estimates often ignore the bias of expectations around a central scenario and may therefore be overly optimistic. In this way, we analyze the impact of uncertainty on the distribution of the expected growth of economic activity in Mexico through the GaR methodology proposed by Adrian et al. (2019). Our results suggest that uncertainty has a negative and statistically significant impact, mainly, on the left tail of the estimated distribution of expected economic growth in Mexico. Likewise, we find that an increase in uncertainty increases the dispersion and shifts the estimated distribution of expected growth to the left, which implies an increase in the probability of observing lower levels of growth. In other words, uncertainty contributes significantly to explaining the negative bias of growth expectations.

Our estimates of IGAE expected growth distribution conditional on the MUI and other economic factors show that, during periods of deep economic recessions, the observed growth of economic activity is more similar to estimates of the lower quantiles of the distribution. Indeed, during the Mexican Peso Crisis of 1994, the Great Financial Crisis of 2008, and the COVID-19 Pandemic, our estimates of the growth distribution show a significant negative bias in growth expectations associated with the high levels of uncertainty during those periods. In this sense, we show that, with higher levels of uncertainty, a relative probability gain is observed when the estimation of the growth distribution is conditioned on the MUI. Likewise, the results show a high vulnerability to low growth, especially during the Mexican Peso Crisis of 1994 and the COVID-19 Pandemic, measured through the Relative Entropy.

Our results are robust to also controlling for measures of financial conditions, uncertainty, and risk exposure in Mexico. In this regard, it stands out that, once we control for the MUI, financial conditions do not have a significant effect on the distribution of growth. We argue that this result may be due to the fact that the measures of financial conditions, for countries like Mexico, could reflect the level of uncertainty. This could be explained by the level of development of the financial system and a greater exposure to risk and volatility.

Finally, we estimate our model with alternative measures of economic activity on the demand, supply and labor market sides. Specifically, indicators of consumption, investment, industrial production, service sector, level of employment, and employment rate were used. Our results hold for these measures and, in addition, reveal a certain heterogeneity in the impact of uncertainty on growth distribution. In particular, investment presents the greatest effect, while employment rate registered the least. In this way, a relevant extension of our analysis could consist of analyzing in greater detail the impact of uncertainty on the distribution of expected growth of indicators listed above and others, possibly at the sector level, in order to identify the risks of growth expectations and its relationship with uncertainty.

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Appendix A Uncertainty and Growth in Mexico through a VAR analysis

This appendix presents more details and some variations of the VAR presented in section 2, in which we analyze the impact of uncertainty (MUI) on IGAE annual growth rate, controlling for other determinants such as FED, FCI, TCN, PCI, GFI and CETES. All variables have a monthly frequency, MUI and FCI are provided by Bank of Mexico; PCI and GFI are taken from the Bank of Economic Information (BIE) from INEGI; and TCN and CETES from the Economic Information System of Bank of Mexico.

This complementary analysis is of interest, since the results of a VAR can be sensitive to changes in i) the number of lags included in its estimation, and ii) the hierarchy of shocks in the Cholesky ordering (that is, the order of the variables based on their contemporary response to shocks in the errors of each variable). In this appendix IRF, HD, and FEVD are presented for two alternative VAR specifications. In the first one, two lags are included, instead of three as suggested by the Akaike Information Criterion. In the second, the order of hierarchy between the FCI and the MUI is exchanged for Cholesky identification. We conclude that the results presented in section 2 hold even in the face of changes in these specifications.

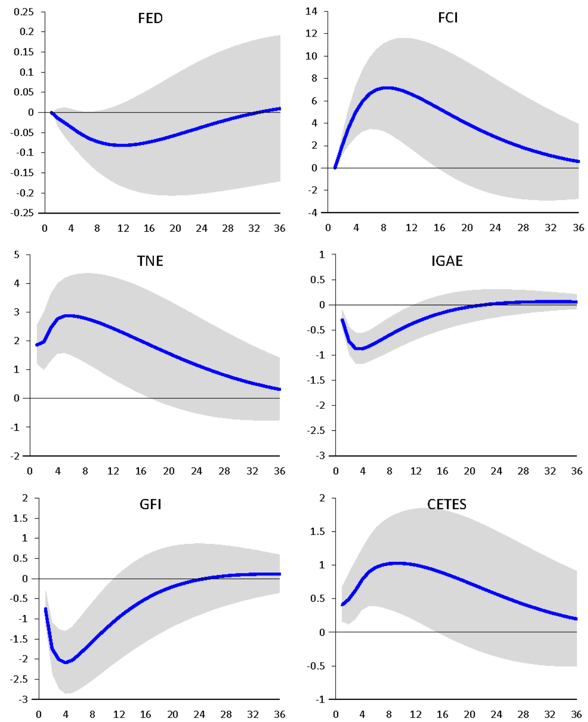
Table 4: Lag Selection Using Information Criterion

Lag	AIC	BIC
1	24.672	25.506
2	23.711	**25.291**
3	**23.591**	25.919
4	23.683	26.763

Source: Own elaboration.

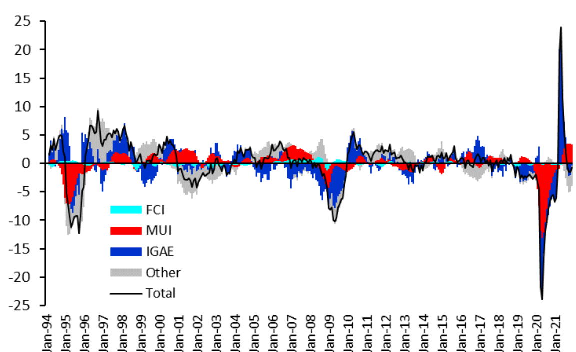
A.1 VAR Results with 2 Lags

Figure 19: Response to Cholesky One S.D (d.f. adjusted) Innovations to MUI

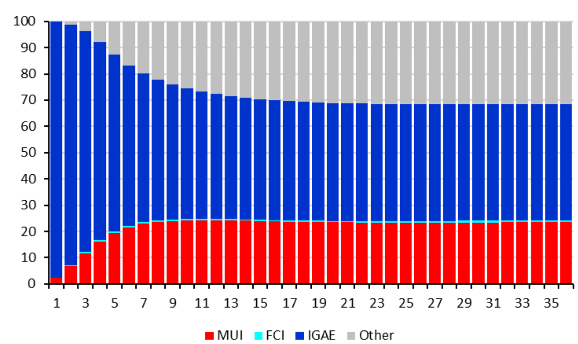


(a) Impulse Response Functions

Notes: Shaded areas represent $\pm$ 2 S.E. confidence intervals.



(b) Historical Decomposition



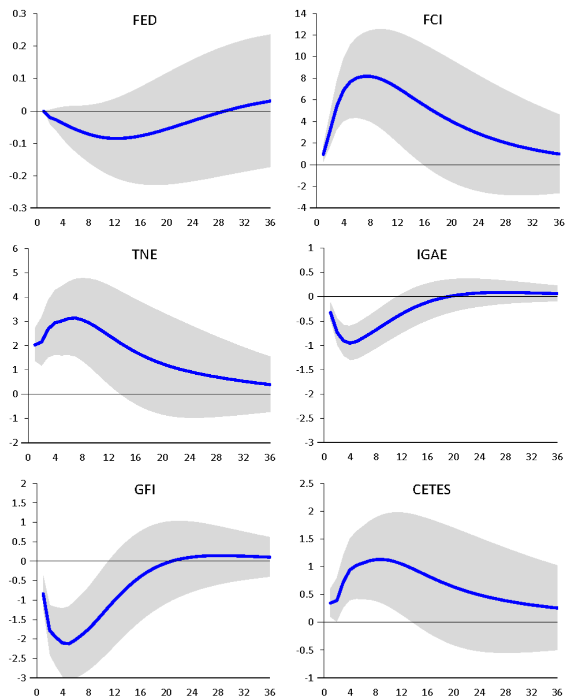
(c) FEVD

Source: Own elaboration.

Notes: Other is the aggregated contribution of FED, TNE, PCI, GFI, CETES.

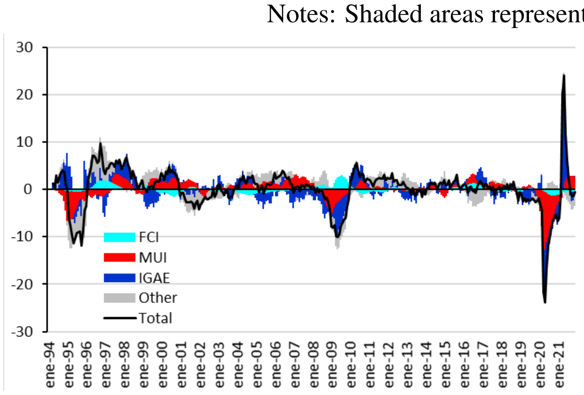
A.2 VAR Results with FCI and MUI Exchanged in the Cholesky Order

Figure 20: Response to Cholesky One S.D (d.f. adjusted) Innovations to MUI

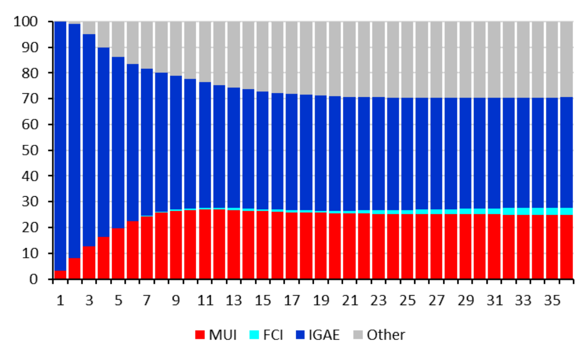


(a) Impulse Response Functions

Notes: Shaded areas represent $\pm$ 2 S.E. confidence intervals..



(b) Historical Decomposition



(c) FEVD

Source: Own elaboration.

Notes: Other is the aggregated contribution of FED, TNE, PCI, GFI, CETES.

Appendix B Robustness Exercises

B.1 US NFCI and Alternative Measures of Risk and Uncertainty in Mexico

This appendix analyzes the robustness of our results regarding the impact of uncertainty on the distribution of expected economic activity through the inclusion in our Benchmark Model of variables related to the state of financial conditions, uncertainty and risk in Mexico. In particular, we estimate through a quantile regression the following equation:

$$y^{\tau}_{t+h} = \alpha_{\tau} + \beta_{\tau} y_t + \delta_{\tau} \pi_t + \gamma_{\tau} IPUS_t + \rho_{\tau} Z_t + \theta_{\tau} MUI_t + \varepsilon^{\tau}_t \tag{12}$$

Where Z_t is the Chicago Fed NFCI used by Adrian et al. (2019) to measure the vulnerability of US growth; the EPU of Mexico, EPU of the US and Global EPU, suggested by Gu et al. (2021) to analyze the downside risk of growth expectations; the nominal exchange rate (NER), the real exchange rate (RER) and the risk premium as more traditional measures of exposure to risk and uncertainty in Mexico, respectively for each estimate. Results suggest that our estimates of the impact of uncertainty on expectations of economic growth in Mexico are robust to the inclusion of these variables.

Table 5: Estimated Coefficients of Benchmark Model with NFCI (h = 3 months)

	10th Quantile			25th Quantile		
	Coef.	Lower	Upper	Coef.	Lower	Upper
Intercept	34.32 ***	23.4	45.2	28.14 ***	20.3	36.0
Inflation	0.18 ***	0.1	0.3	0.21 ***	0.1	0.3
IPUS	0.18 **	0.0	0.3	0.05	0.0	0.1
MUI	-0.51 ***	-0.7	-0.4	-0.42 ***	-0.5	-0.3
IGAE	0.35 ***	0.2	0.5	0.50 ***	0.4	0.6
NFCI	0.05	-0.9	1.0	-0.23	-0.8	0.3

	50th Quantile			90th Quantile		
	Coef.	Lower	Upper	Coef.	Lower	Upper
Intercept	16.50 ***	8.8	24.2	-1.22	-6.7	4.3
Inflation	0.17 ***	0.1	0.2	0.08 ***	0.0	0.1
IPUS	0.00	-0.1	0.1	-0.02	-0.2	0.1
MUI	-0.24 ***	-0.4	-0.1	0.04	0.0	0.1
IGAE	0.61 ***	0.5	0.7	0.54 ***	0.4	0.7
NFCI	-0.92 ***	-1.4	-0.4	-1.22 **	-2.1	-0.4

Source: Own elaboration.
Notes "***", "**", "*" if $p < 0.01$, $p < 0.05$, and $p < 0.1$, respectively. Lower and Upper indicate the 90% confidence interval built by bootstrap.

Table 6: Estimated Coefficients of Benchmark Model with EPU (h = 3 months)

	10th Quantile			25th Quantile		
	Coef.	Lower	Upper	Coef.	Lower	Upper
Intercept	42.77 ***	28.6	56.9	25.30 ***	15.8	34.8
Inflation	0.31 ***	0.2	0.4	0.22 ***	0.2	0.3
IPUS	0.19 **	0.1	0.3	0.20 ***	0.1	0.3
MUI	-0.64 ***	-0.9	-0.4	-0.37 ***	-0.5	-0.2
IGAE	0.08	-0.1	0.2	0.24 **	0.1	0.4
EPU	0.00	0.0	0.0	0.00	0.0	0.0

	50th Quantile			90th Quantile		
	Coef.	Lower	Upper	Coef.	Lower	Upper
Intercept	11.03 *	0.4	21.6	0.81	-10.1	11.7
Inflation	0.16 ***	0.1	0.2	0.10 ***	0.0	0.2
IPUS	0.22 ***	0.1	0.3	0.03	-0.2	0.2
MUI	-0.15	-0.3	0.0	0.03	-0.1	0.2
IGAE	0.28 **	0.1	0.5	0.48 ***	0.3	0.7
EPU	0.00 *	0.0	0.0	-0.01 *	0.0	0.0

Source: Own elaboration.
Notes "***", "**", "*" if $p < 0.01$, $p < 0.05$, and $p < 0.1$, respectively. Lower and Upper indicate the 90% confidence interval built by bootstrap.

Table 7: Estimated Coefficients of Benchmark Model with EPU US (h = 3 months)

	10th Quantile			25th Quantile		
	Coef.	Lower	Upper	Coef.	Lower	Upper
Intercept	35.09 ***	28.3	41.9	29.70 ***	24.3	35.1
Inflation	0.16 **	0.0	0.3	0.19 ***	0.1	0.3
IPUS	0.11 *	0.0	0.2	0.08 **	0.0	0.1
MUI	-0.50 ***	-0.6	-0.4	-0.43 ***	-0.5	-0.3
IGAE	0.34 **	0.1	0.6	0.41 ***	0.3	0.5
EPU US	-0.01 **	0.0	0.0	0.00 *	0.0	0.0

	50th Quantile			90th Quantile		
	Coef.	Lower	Upper	Coef.	Lower	Upper
Intercept	16.90 ***	7.9	25.9	-1.41	-7.1	4.2
Inflation	0.15 ***	0.1	0.2	0.08 ***	0.1	0.1
IPUS	0.04	-0.1	0.1	-0.06	-0.2	0.1
MUI	-0.23 ***	-0.4	-0.1	0.06	0.0	0.1
IGAE	0.56 ***	0.4	0.7	0.53 ***	0.4	0.7
EPU US	0.00	0.0	0.0	0.00	0.0	0.0

Source: Own elaboration.
Notes "***", "**", "*" if $p < 0.01$, $p < 0.05$, and $p < 0.1$, respectively. Lower and Upper indicate the 90% confidence interval built by bootstrap.

Table 8: Estimated Coefficients of Benchmark Model with EPU Global (h = 3 months)

	10th Quantile			25th Quantile		
	Coef.	Lower	Upper	Coef.	Lower	Upper
Intercept	37.09 ***	23.6	50.6	24.29 ***	16.1	32.5
Inflation	0.25 ***	0.1	0.4	0.15 ***	0.1	0.2
IPUS	0.21 **	0.0	0.4	0.22 ***	0.1	0.3
MUI	-0.53 ***	-0.7	-0.3	-0.34 ***	-0.5	-0.2
IGAE	0.07	-0.2	0.3	0.22 *	0.0	0.4
EPU Global	-0.01 ***	0.0	0.0	-0.01 ***	0.0	0.0

	50th Quantile			90th Quantile		
	Coef.	Lower	Upper	Coef.	Lower	Upper
Intercept	13.34 **	4.7	22.0	0.63	-10.4	11.7
Inflation	0.10 *	0.0	0.2	0.07	0.0	0.2
IPUS	0.19 ***	0.1	0.3	0.01	-0.2	0.2
MUI	-0.17 **	-0.3	0.0	0.04	-0.1	0.2
IGAE	0.36 ***	0.2	0.5	0.44 ***	0.2	0.7
EPU Global	-0.01 ***	0.0	0.0	-0.01	0.0	0.0

Source: Own elaboration.
Notes "***", "**", "*" if $p < 0.01$, $p < 0.05$, and $p < 0.1$, respectively. Lower and Upper indicate the 90% confidence interval built by bootstrap.

Table 9: Estimated Coefficients of Benchmark Model with TNE (h = 3 months)

	10th Quantile			25th Quantile		
	Coef.	Lower	Upper	Coef.	Lower	Upper
Intercept	41.34 ***	31.0	51.7	32.80 ***	26.3	39.3
Inflation	0.16 **	0.1	0.3	0.19 ***	0.1	0.2
IPUS	0.10	0.0	0.2	0.09 **	0.0	0.2
MUI	-0.56 ***	-0.7	-0.4	-0.46 ***	-0.5	-0.4
IGAE	0.33 **	0.1	0.6	0.38 ***	0.2	0.5
NER	-0.24 ***	-0.4	-0.1	-0.10 **	-0.2	0.0

	50th Quantile			90th Quantile		
	Coef.	Lower	Upper	Coef.	Lower	Upper
Intercept	21.99 ***	12.8	31.2	2.96	-7.9	13.8
Inflation	0.15 ***	0.1	0.2	0.09 ***	0.1	0.1
IPUS	0.04	-0.1	0.1	-0.09	-0.3	0.1
MUI	-0.30 ***	-0.4	-0.2	0.01	-0.1	0.1
IGAE	0.54 ***	0.4	0.7	0.52 ***	0.4	0.6
NER	-0.09 **	-0.2	0.0	-0.10	-0.3	0.1

Source: Own elaboration.
Notes "***", "**", "*" if $p < 0.01$, $p < 0.05$, and $p < 0.1$, respectively. Lower and Upper indicate the 90% confidence interval built by bootstrap.

Table 10: Estimated Coefficients of Benchmark Model with RER (h = 3 months)

	10th Quantile			25th Quantile		
	Coef.	Lower	Upper	Coef.	Lower	Upper
Intercept	38.37 ***	27.1	49.6	29.28 ***	23.5	35.1
Inflation	0.21 ***	0.1	0.3	0.20 ***	0.1	0.3
IPUS	0.13	0.0	0.3	0.11 ***	0.0	0.2
MUI	-0.52 ***	-0.7	-0.4	-0.40 ***	-0.5	-0.3
IGAE	0.31 **	0.1	0.6	0.41 ***	0.3	0.5
RER	-0.04 **	-0.1	0.0	-0.02 **	0.0	0.0

	50th Quantile			90th Quantile		
	Coef.	Lower	Upper	Coef.	Lower	Upper
Intercept	19.25 ***	9.7	28.8	-0.91	-9.1	7.3
Inflation	0.17 ***	0.1	0.2	0.08 **	0.0	0.1
IPUS	0.05	-0.1	0.1	-0.02	-0.2	0.2
MUI	-0.26 ***	-0.4	-0.1	0.03	-0.1	0.1
IGAE	0.56 ***	0.4	0.7	0.55 ***	0.4	0.7
RER	-0.01	0.0	0.0	0.01	0.0	0.1

Source: Own elaboration.
Notes "***", "**", "*" if $p < 0.01$, $p < 0.05$, and $p < 0.1$, respectively. Lower and Upper indicate the 90% confidence interval built by bootstrap.

Table 11: Estimated Coefficients of Benchmark Model with Risk Premium (h = 3 months)

	10th Quantile			25th Quantile		
	Coef.	Lower	Upper	Coef.	Lower	Upper
Intercept	40.93 ***	28.6	53.3	31.31 ***	22.3	40.3
Inflation	0.12 *	0.0	0.2	0.19 ***	0.1	0.3
IPUS	0.11	0.0	0.2	0.07	0.0	0.2
MUI	-0.61 ***	-0.8	-0.4	-0.46 ***	-0.6	-0.3
IGAE	0.36 ***	0.2	0.6	0.43 ***	0.3	0.6
Risk Premium	0.12 *	0.0	0.2	0.03	-0.1	0.1

	50th Quantile			90th Quantile		
	Coef.	Lower	Upper	Coef.	Lower	Upper
Intercept	12.41 **	3.2	21.6	-0.08	-6.2	6.1
Inflation	0.21 ***	0.1	0.3	0.15 ***	0.1	0.2
IPUS	0.10	0.0	0.2	-0.02	-0.2	0.1
MUI	-0.17 **	-0.3	0.0	0.04	-0.1	0.1
IGAE	0.51 ***	0.3	0.7	0.54 ***	0.4	0.7
Risk Premium	-0.10 *	-0.2	0.0	-0.08	-0.2	0.0

Source: Own elaboration.
Notes "***", "**", "*" if $p < 0.01$, $p < 0.05$, and $p < 0.1$, respectively. Lower and Upper indicate the 90% confidence interval built by bootstrap.

B.2 Estimates with Alternative Measures of Economic Activity

Finally, in this section we use alternative measures of the level of economic activity in Mexico, in order to assess whether our results are robust to the inclusion of these indicators. For these exercises we use six indicators, two on the demand side, two on the supply side and two on the labor market side. First, on the demand side, we include the monthly indicators of private consumption (CONS) and gross fixed investment (INV) from INEGI. On the supply side, we include the monthly indicator of industrial activity (IMAI) and the IGAE of the tertiary sector (SERV) from INEGI. Finally, on the labor market side, we include the level of formal employment in the economy as a whole measured through the number of jobs affiliated with the Mexican Social Security Institute (IMSS) and the employment rate (EMP) measured as 100-TD, where TD is the national monthly unemployment rate from INEGI. For the analysis of these exercises, the following variation of the Benchmark Model is estimated by a quantile regression:

$$z^{\tau}_{t+h} = \alpha_{\tau} + \beta_{\tau} z_t + \delta_{\tau} \pi_t + \gamma_{\tau} IPUS_t + \theta_{\tau} MUI_t + \varepsilon^{\tau}_t \tag{13}$$

Where z_t is the annual percentage growth rate of the CONS, INV, IMAI, SERV, IMSS or the annual variation rate of the EMP. The estimates of these models show that our main result about the impact of uncertainty on the distribution of the expected growth of the IGAE is robust to the use of different measures to approximate economic activity in Mexico.

Table 12: Estimated Coefficients of Model with Consumption (h = 3 months)

	10th Quantile			25th Quantile		
	Coef.	Lower	Upper	Coef.	Lower	Upper
Intercept	31.62 ***	16.3	46.9	21.69 ***	16.4	27.0
Inflation	0.19 ***	0.1	0.3	0.15 ***	0.1	0.2
IPUS	0.06	-0.1	0.2	0.05	0.0	0.1
MUI	-0.48 ***	-0.7	-0.3	-0.32 ***	-0.4	-0.2
CONS	0.55 ***	0.4	0.7	0.49 ***	0.4	0.6

	50th Quantile			90th Quantile		
	Coef.	Lower	Upper	Coef.	Lower	Upper
Intercept	15.30 ***	8.1	22.5	-0.43	-7.6	6.8
Inflation	0.13 ***	0.1	0.2	0.03	0.0	0.1
IPUS	0.04	0.0	0.1	0.01	-0.1	0.1
MUI	-0.21 ***	-0.3	-0.1	0.05	-0.1	0.2
CONS	0.48 ***	0.4	0.6	0.58 ***	0.4	0.7

Source: Own elaboration.
Notes "***", "**", "*" if $p < 0.01$, $p < 0.05$, and $p < 0.1$, respectively. Lower and Upper indicate the 90% confidence interval built by bootstrap.

Table 13: Estimated Coefficients of Model with Investment (h = 3 months)

	10th Quantile			25th Quantile		
	Coef.	Lower	Upper	Coef.	Lower	Upper
Intercept	72.97 ***	29.9	116.0	60.81 ***	39.7	81.9
Inflation	0.57 ***	0.2	0.9	0.46 ***	0.2	0.7
IPUS	-0.27	-0.5	0.0	-0.12	-0.3	0.0
MUI	-1.16 ***	-1.8	-0.5	-0.93 ***	-1.2	-0.6
INV	0.65 ***	0.5	0.8	0.68 ***	0.6	0.8

	50th Quantile			90th Quantile		
	Coef.	Lower	Upper	Coef.	Lower	Upper
Intercept	51.80 ***	24.8	78.8	12.78	-5.9	31.5
Inflation	0.49 ***	0.2	0.7	0.41 ***	0.3	0.6
IPUS	0.00	-0.3	0.3	-0.19	-0.5	0.1
MUI	-0.77 ***	-1.2	-0.4	-0.12	-0.4	0.2
INV	0.67 ***	0.5	0.8	0.63 ***	0.5	0.7

Source: Own elaboration.
Notes "***", "**", "*" if $p < 0.01$, $p < 0.05$, and $p < 0.1$, respectively. Lower and Upper indicate the 90% confidence interval built by bootstrap.

Table 14: Estimated Coefficients of Model with Industrial Production (h = 3 months)

	10^{th} Quantile			25^{th} Quantile		
	Coef.	Lower	Upper	Coef.	Lower	Upper
Intercept	41.40 ***	33.9	49.0	35.68 ***	25.9	45.4
Inflation	0.22 **	0.1	0.4	0.27 ***	0.2	0.4
IPUS	0.14 *	0.0	0.3	0.07	0.0	0.2
MUI	-0.64 ***	-0.8	-0.5	-0.54 ***	-0.7	-0.4
IMAI	0.28 **	0.1	0.5	0.39 ***	0.2	0.6

	50^{th} Quantile			90^{th} Quantile		
	Coef.	Lower	Upper	Coef.	Lower	Upper
Intercept	21.38 ***	7.8	34.9	-1.83	-10.4	6.7
Inflation	0.27 ***	0.2	0.4	0.17 ***	0.1	0.2
IPUS	0.09	-0.1	0.2	-0.17	-0.5	0.1
MUI	-0.32 ***	-0.5	-0.1	0.06	-0.1	0.2
IMAI	0.49 ***	0.3	0.7	0.54 ***	0.4	0.7

Source: Own elaboration.
Notes “***”, “**”, “*” if $p < 0.01$, $p < 0.05$, and $p < 0.1$, respectively. Lower and Upper indicate the 90% confidence interval built by bootstrap.

Table 15: Estimated Coefficients of Model with Services (h = 3 months)

	10^{th} Quantile			25^{th} Quantile		
	Coef.	Lower	Upper	Coef.	Lower	Upper
Intercept	32.68 ***	20.0	45.4	23.94 ***	19.7	28.2
Inflation	0.17 ***	0.1	0.3	0.15 ***	0.1	0.2
IPUS	0.08	0.0	0.2	0.12 **	0.0	0.2
MUI	-0.48 ***	-0.7	-0.3	-0.35 ***	-0.4	-0.3
Services	0.45 ***	0.2	0.7	0.46 ***	0.3	0.6

	50^{th} Quantile			90^{th} Quantile		
	Coef.	Lower	Upper	Coef.	Lower	Upper
Intercept	16.61 ***	8.3	24.9	2.42	-3.7	8.6
Inflation	0.12 ***	0.1	0.2	0.04 *	0.0	0.1
IPUS	0.08 *	0.0	0.1	0.05	-0.1	0.2
MUI	-0.23 ***	-0.3	-0.1	0.00	-0.1	0.1
Services	0.50 ***	0.4	0.6	0.48 ***	0.3	0.6

Source: Own elaboration.
Notes “***”, “**”, “*” if $p < 0.01$, $p < 0.05$, and $p < 0.1$, respectively. Lower and Upper indicate the 90% confidence interval built by bootstrap.

Table 16: Estimated Coefficients of Model with Employment Level (h = 3 months)

	10th Quantile			25th Quantile		
	Coef.	Lower	Upper	Coef.	Lower	Upper
Intercept	20.30 ***	12.6	28.0	15.28 ***	11.4	19.2
Inflation	0.11	-0.1	0.3	0.12 ***	0.1	0.2
IPUS	0.09 **	0.0	0.2	0.10 ***	0.1	0.1
MUI	-0.30 ***	-0.4	-0.2	-0.22 ***	-0.3	-0.2
IMSS	0.78 ***	0.7	0.9	0.69 ***	0.6	0.8

	50th Quantile			90th Quantile		
	Coef.	Lower	Upper	Coef.	Lower	Upper
Intercept	7.24 ***	3.1	11.4	2.58	-1.7	6.9
Inflation	0.05 *	0.0	0.1	0.06 **	0.0	0.1
IPUS	0.11 ***	0.1	0.1	0.10 ***	0.1	0.1
MUI	-0.10 ***	-0.2	0.0	-0.01	-0.1	0.1
IMSS	0.72 ***	0.7	0.8	0.52 ***	0.3	0.7

Source: Own elaboration.
Notes "***", "**", "*" if $p < 0.01$, $p < 0.05$, and $p < 0.1$, respectively. Lower and Upper indicate the 90% confidence interval built by bootstrap.

Table 17: Estimated Coefficients of Model with Employment Rate (h = 3 months)

	10th Quantile			25th Quantile		
	Coef.	Lower	Upper	Coef.	Lower	Upper
Intercept	4.96 ***	4.0	5.9	5.53 ***	4.0	7.0
Inflation	0.03 ***	0.0	0.0	0.04 ***	0.0	0.1
IPUS	0.00	0.0	0.0	0.00	0.0	0.0
MUI	-0.08 ***	-0.1	-0.1	-0.09 ***	-0.1	-0.1
EMP	0.68 ***	0.6	0.8	0.70 ***	0.6	0.8

	50th Quantile			90th Quantile		
	Coef.	Lower	Upper	Coef.	Lower	Upper
Intercept	3.32 ***	1.3	5.3	2.04 ***	1.1	3.0
Inflation	0.04 ***	0.0	0.1	0.04 ***	0.0	0.1
IPUS	0.00	0.0	0.0	-0.01	0.0	0.0
MUI	-0.05 ***	-0.1	0.0	-0.03 ***	0.0	0.0
EMP	0.67 ***	0.6	0.8	0.67 ***	0.6	0.8

Source: Own elaboration.
Notes "***", "**", "*" if $p < 0.01$, $p < 0.05$, and $p < 0.1$, respectively. Lower and Upper indicate the 90% confidence interval built by bootstrap.

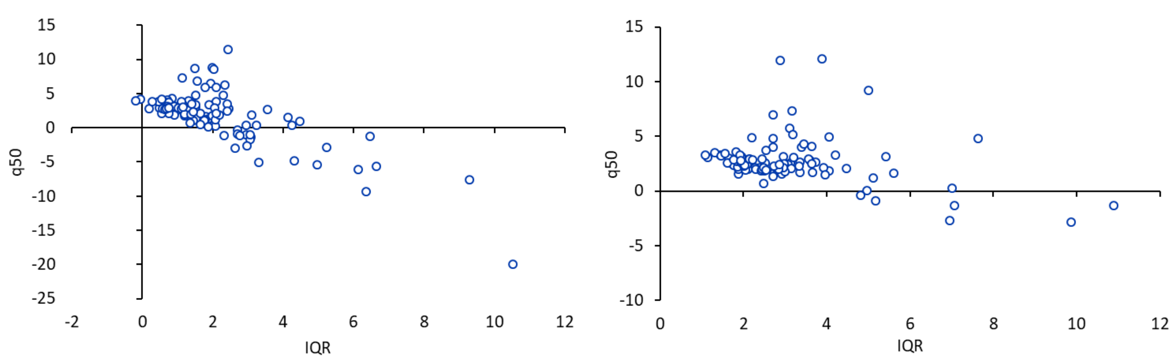
Appendix C Estimates Based on Mexico's GDP

This appendix presents some results of the analysis of our Benchmark Model with Mexico's GDP. The exercise was carried out for a quarterly sample from 1994Q1 to 2021Q4, with data on the annual growth rate of Mexico's GDP from INEGI. The series of the IPUS, INPC and MUI were aggregated to a quarterly frequency through a simple average to later calculate the annual growth rates of the IPUS and INPC (to obtain the annual inflation, INF). All series are seasonally adjusted at their original level and frequency. In particular, the following quantile regression was estimated:

$$GDP_{t+h}^{\tau} = \alpha_{\tau} + \beta_{\tau} GDP_t + \delta_{\tau} INF_t + \gamma_{\tau} IPUS_t + \theta_{\tau} MUI_t + \varepsilon_t^{\tau} \tag{14}$$

The estimates of the previous equation can be observed in Table 18. The results are consistent with those obtained based on IGAE. In particular, the coefficients associated with the MUI are negative and statistically significant for the left tail of the distribution of expected GDP growth. The marginal effect of an increase of one unit in the MUI in the tenth quantile with a forecast of one quarter ahead is -0.34 pp, similar to that obtained with the IGAE with a forecast of three months ahead. The significance of the results associated with the MUI is sustained for horizons of two, three and four quarters. It is also possible to associate both an increase in dispersion and a shift in the estimated distribution of expected GDP growth to an increase in uncertainty. In this regard, Figure 21 shows the relationship between the interquartile range and the median of the estimated distribution for forecast horizons of one and four quarters. Finally, as in the case of the estimates based on IGAE, we can also analyze the effect of uncertainty on growth through the estimates of the density and cumulative distribution function for each period of the analysis. Thus, in Figure 22 we present the cumulative density and distribution of expected GDP growth for the second quarter of 2020, a period in which the deepest drop in Mexico's GDP was observed associated with the effects of the COVID-19 pandemic.

Figure 21: Median and Interquartile Range Scatterplot of Quantile Regression with GDP



(a) One quarter ahead

(b) Four quarters ahead

Source: Own elaboration.

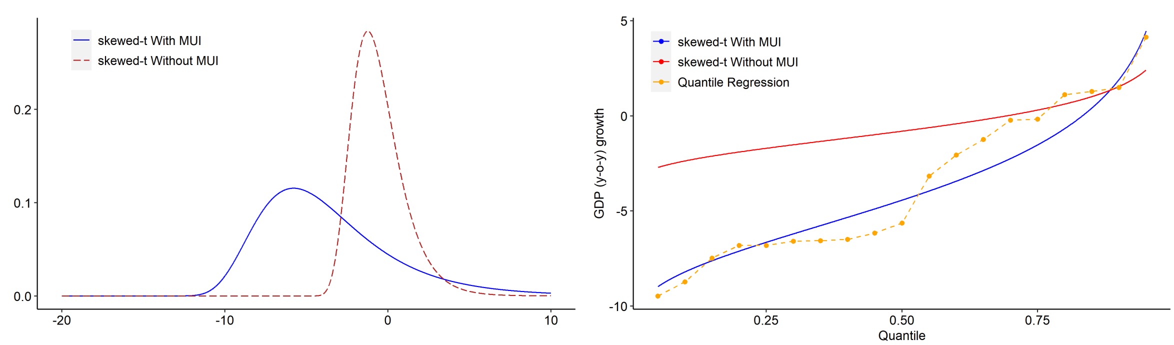
Table 18: Estimated Coefficients of Model with GDP (yoy) growth (h = 1 quarter)

	10th Quantile			25th Quantile		
	Coef.	Lower	Upper	Coef.	Lower	Upper
Intercepto	37.32 **	10.0	64.7	27.37 ***	17.8	37.0
Inflation	0.27 *	0.0	0.5	0.21 ***	0.1	0.3
IPUS	0.08	-0.1	0.3	0.08	0.0	0.2
MUI	-0.56 **	-1.0	-0.1	-0.41 ***	-0.5	-0.3
GDP	0.34 *	0.0	0.7	0.56 ***	0.3	0.8

	50th Quantile			90th Quantile		
	Coef.	Lower	Upper	Coef.	Lower	Upper
Intercepto	26.69 ***	10.4	43.0	3.56	-7.5	14.6
Inflation	0.23 ***	0.1	0.4	0.12 ***	0.0	0.2
IPUS	0.01	-0.1	0.2	-0.18	-0.5	0.1
MUI	-0.39 **	-0.6	-0.1	-0.02	-0.2	0.1
GDP	0.56 ***	0.3	0.8	0.69 ***	0.4	1.0

Source: Own elaboration.
Notes "***", "**", "*" if $p < 0.01$, $p < 0.05$, and $p < 0.1$, respectively. Lower and Upper indicate the 90% confidence interval built by bootstrap.

Figure 22: Density and Distribution Functions During 2020-Q2



(a) Probability Density Function (b) Cumulative Distribution Function

Source: Own elaboration.

Appendix D A GaR model based on the FCI of Mexico

In this section, we follow the econometric specification of the works by Banxico (2019), Banxico (2020a), and Adrian et al. (2019) in order to estimate a FCI-based GaR model for Mexico built by Carrillo and García (2021). To carry out this exercise, the following quantile regression is estimated:

$$y^{\tau}_{t+h} = \alpha_{\tau} + \beta_{\tau} y_t + \delta_{\tau} \pi_t + \gamma_{\tau} FCI_t + \varepsilon^{\tau}_t \tag{15}$$

Where y_t is the IGAE annual growth rate, π_t is inflation measured as the INPC annual growth rate and IFC_t is the FCI of Mexico. The subscript h indicates the forecast horizon of the regression and the superscript τ indicates the quantile being estimated, with discrete values from 0.05 to 0.95, in 0.05 intervals. Figure 19 shows the estimated coefficients of the previous equation for a forecast horizon of one and three months. The results are similar to those found by Banxico (2019) and Banxico (2020a), and suggest some evidence that financial conditions in Mexico could impact the distribution of expected economic growth. In particular, based on these results, it could be inferred that the FCI may be a good indicator to measure the negative bias of economic growth expectations in Mexico.

Table 19: Estimated Coefficients of Benchmark Model based on FCI (h = 3 months)

	10th Quantile			25th Quantile		
	Coef.	Lower	Upper	Coef.	Lower	Upper
Intercept	-0.88	-2.1	0.4	-0.60 *	-1.1	-0.1
IPUS	0.21	0.0	0.4	0.07	-0.1	0.2
IGAE	0.49 **	0.1	0.8	0.64 ***	0.4	0.9
Inflation	-0.07	-0.2	0.1	0.04	0.0	0.1
FCI	-0.01	0.0	0.0	-0.01 **	0.0	0.0

	50th Quantile			90th Quantile		
	Coef.	Lower	Upper	Coef.	Lower	Upper
Intercept	0.10	-0.3	0.5	2.44 ***	1.9	3.0
IPUS	0.05	-0.1	0.2	-0.04	-0.2	0.1
IGAE	0.58 ***	0.4	0.7	0.52 ***	0.4	0.7
Inflation	0.09 **	0.0	0.1	0.10 ***	0.1	0.1
FCI	-0.01 **	0.0	0.0	0.00	0.0	0.0

Source: Own elaboration.
Notes "***", "**", "*" if $p < 0.01$, $p < 0.05$, and $p < 0.1$, respectively. Lower and Upper indicate the 90% confidence interval built by bootstrap.