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N° 2023-08

## Growth at Risk and Uncertainty: Evidence from Mexico

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## Growth at Risk and Uncertainty: Evidence from Mexico\*

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**Abstract:** We analyze the relationship between uncertainty and economic growth expectations in Mexico through the Growth at Risk methodology. Our analysis consists of two stages: first, we estimate a quantile regression of annual output growth conditional on lagged values of a measure of macroeconomic uncertainty and other drivers. Second, based on the fitted values of the quantile regression, we estimate the parameters of a t-skewed distribution of expected economic growth. Our results show that an increase in macroeconomic uncertainty has a negative and statistically significant impact on the left tail of the growth distribution, leading to an increased probability of observing lower growth rates. These results remain robust to alternative measures of financial conditions, of economic policy uncertainty, and of risk exposure, as well as to alternative measurements of economic activity.

**Keywords:** Macroeconomic Uncertainty; Financial Conditions; Growth at Risk.

**JEL Classification:** C53, E23, E27, E32, O40.

**Resumen:** Analizamos la relación entre la incertidumbre y las expectativas de crecimiento económico en México a través de la metodología de Crecimiento en Riesgo. Nuestro análisis consta de dos etapas: primero, estimamos una regresión cuantílica del crecimiento anual del producto condicionada en valores rezagados de una medida de incertidumbre macroeconómica y otros factores. En segundo lugar, con base en los valores ajustados de la regresión cuantílica, estimamos los parámetros de una distribución t-sesgada del crecimiento económico esperado. Nuestros resultados muestran que un aumento en la incertidumbre macroeconómica tiene un impacto negativo y estadísticamente significativo en la cola izquierda de la distribución del crecimiento, lo que lleva a una mayor probabilidad de observar tasas de crecimiento más bajas. Estos resultados siguen siendo robustos a medidas alternativas de condiciones financieras, de incertidumbre de política económica y de exposición al riesgo, así como a medidas alternativas de actividad económica.

**Palabras Clave:** Incertidumbre Macroeconómica; Condiciones Financieras; Crecimiento en Riesgo

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# 1 Introduction

In recent decades, the Mexican economy has been exposed to several episodes of high uncertainty associated with internal and external factors. Given the magnitude of the uncertainty shocks to which the Mexican economy has been exposed, and the fact that high uncertainty could be associated with growth at risk and vulnerability of growth it is relevant to analyze their impact on growth expectations from an empirical perspective, contributing to the understanding of factors that could bias growth expectations and the channels through which uncertainty impacts the real economy. This paper contributes to the growing literature on the empirical analysis of the relationship between macroeconomic uncertainty and economic growth expectations. Our analysis is carried out by means of the Growth at Risk (GaR) methodology proposed by Adrian et al. (2019)<sup>1</sup> applied to the case of Mexico.

Related literature, mostly focused on the case of the United States and on emerging economies such as China, has emphasized the role of uncertainty as an essential determinant of economic growth and growth expectations (See for instance, Bloom (2009); Bloom (2014); Bonciani and Jason (2019); Jovanovic and Ma (2020); Gu et al. (2021)). According to those studies, an environment of high uncertainty can have important adverse effects associated with the decision-making of economic agents on the macroeconomy, microeconomy and financial markets. Thus, uncertainty shocks would significantly impact growth expectations through the precautionary behavior of economic agents that would delay their consumption and investment plans while waiting for better conditions. Examples of the effects of high uncertainty on economic agents' decisions include:

- Firms delaying their investing and hiring plans due to the expectation of more uncertain returns.

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<sup>1</sup>The main strength of GaR methodology is its ability to assess the entire distribution of expected GDP growth and monitor the evolution of risks to economic activity over time. By using GaR analysis, policymakers can quantify the likelihood of risk scenarios, which would serve as a basis for preemptive action (See Prasad et al. (2019)). Another tool usually used to analyze expected growth distributions is the 'fan charts' that convey uncertainty around central projections from linearised macroeconomic models. Recent literature has shown that GaR models provide improved estimates of the left-tail of the GDP growth distribution, particularly at medium-term horizons, compared to the GDP fan charts. However, GaR models generally perform worse than the fan charts at the center of the distribution (See Lloyd et al. (2022)). In this way, it has been shown that by combining both methodologies, a better projection of the complete distribution of expected GDP growth could be obtained.

- Households increasing their savings as a precautionary measure, resulting in reduced consumption.
- Increased financing cost driven by the expectation of higher risk premia.
- Reduced responsiveness to interest rate variations, reducing the effectiveness of monetary policy.<sup>2</sup>

It seems plausible that increases in uncertainty of the economy would not only affect point estimates of forecasted economic growth, but also affects its entire probability distribution<sup>3</sup>, possibly generating a bias in expected growth (Adrian et al. (2019); Prasad et al. (2019)). Adrian et al. (2019) were among the first to analyze the United States (U.S.) GDP growth expectations by means of the GaR methodology. Adrian et al. (2019) empirically model the probability distribution of expected GDP growth as a function of observable economic conditions and financial conditions. To approximate the financial conditions in the U.S., 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 measurements of the bias in economic growth expectations in order to quantify the downward and upward vulnerability of expected GDP growth.

For the case of Mexico, some studies have provided evidence about the impact of financial conditions on the distribution of economic growth. For instance, Banxico (2019) and Banxico (2020a) discuss the risks associated with financial conditions for economic growth in Mexico.<sup>4</sup> 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) shifted to the left as a result of the tightening of financial conditions and the slowdown in economic activity in Mexico.

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<sup>2</sup>Aquino et al. (2022) analyze the impact of monetary policy in the United States under high and low uncertainty regimes. Findings indicate that in low uncertainty periods, the U.S. Monetary policy is effective since it drops economic activity and inflation. In contrast, in the high uncertainty regime, the U.S. Monetary policy loses its effectiveness since it does not affect, or has a reduced effect, on economic activity and inflation.

<sup>3</sup>For instance, policymakers, such as central banks and multilateral international organizations, such as the International Monetary Fund and the World Bank, provide not only point 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.

<sup>4</sup>These analysis use a non-public financial conditions index estimated by the Bank of Mexico.

Unlike the traditional approach of GaR methodology that emphasizes the role of financial conditions on expected growth, in our paper we focus on the impact of macroeconomic uncertainty on economic growth expectations. Our approach is based on two main observations. On the one hand, it is possible that financial variables are not entirely adequate to analyze expected economic growth. In a recent paper, Plagborg-Møller et al. (2020) show evidence that financial variables have 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. On the other hand, it is possible that a tightening of financial conditions and its effect over expected economic growth could be itself a reflection of an increase in the level of uncertainty.<sup>5</sup> For instance, in environments of greater uncertainty, firms and households could face more restrictive credit and liquidity conditions. There could be a tightening of conditions for obtaining credit, such as a greater aversion of banks to grant loans and higher costs of credit access that could affect economic activity performance.

Several papers have analyzed the impact of uncertainty on various macroeconomic variables in Mexico. However, to the best of our knowledge, there is no paper that analyzes the impact of uncertainty on the complete distribution of expected economic growth in Mexico. For instance, López and Bush (2019) investigate the effect of uncertainty on exchange rate volatility for 1999 - 2018 in Mexico using survey-based indicators of uncertainty. They show that greater uncertainty leads to higher exchange rate volatility and find evidence of an amplifying effect of domestic economic uncertainty on exchange rate volatility, especially during periods of recession. Catalán (2019) analyzes the impact of uncertainty shocks on economic activity in Mexico. He shows that shocks of economic policy uncertainty (EPU) increase prices and interest rates and reduce investment and employment. Finally, Cebberos et al. (2020) analyze the impact of a particular type of uncertainty, trade policy uncertainty (TPU), on foreign direct investment (FDI). The authors find that the increase in TPU was associated with a negative effect on FDI inflows, with the effect being driven by the negative impact that TPU had on FDI in export-oriented states in Mexico. Given that uncertainty seems to be an important determinant of economic activity, we analyze its impact on the full distribution of expected growth in Mexico.

To quantify the level of uncertainty in Mexico, we use the Macroeconomic Uncertainty Index for Mexico (MUI), estimated by the Bank of Mexico, based on the methodology

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<sup>5</sup>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) had a high positive correlation since 2009, which could be a reflection of the effect of external uncertainty on financial conditions in Mexico.

of Jurado et al. (2015).<sup>6</sup> The MUI is a weighted average of the volatility of the forecast errors of 125 macroeconomic variables. An increase in this index implies that, on average, it is more difficult to predict the behavior of the economy at a given moment of time, which is interpreted as an increase in macroeconomic uncertainty. To examine the empirical relationship between macroeconomic uncertainty and the distribution of growth in Mexico, a GaR-type analysis relating the annual growth rate of the IGAE <sup>7</sup> with the MUI and other determinants of growth is carried out.<sup>8</sup> To do this, following Adrian et al. (2019), we perform a two-stage estimation. 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 U.S. industrial production index (IPUS) or inflation).<sup>9</sup> These estimates allow us to analyze the marginal impact of uncertainty along the conditional distribution of growth for each period of the sample.<sup>10</sup> In the second stage, the parameters of a *skewed – t* distribution of expected 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 expected 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.

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<sup>6</sup>For more details about the methodology to construct the MUI for Mexico and the variables included in its estimation, see Banxico (2020b).

<sup>7</sup>The Global Indicator of Economic Activity (IGAE) is a monthly series that measures the real sector of the economy. 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 is constructed at a monthly frequency to better capture the state and variations of uncertainty in the economy.

<sup>8</sup>Even when the MUI is built from information that includes a set of variables related to economic activity, we consider that the MUI should not present a significant endogeneity problem with the IGAE. First, the MUI is constructed as the simple average of the forecast errors of more than 100 variables representing the situation of the Mexican economy. In this sense, by construction it seems unlikely that the IGAE significantly affects those forecast errors, leading to a significant problem of endogeneity of our quantile regressions. Second, in order to mitigate a possible endogeneity problem, we also use controls that help us mitigate this problem in our quantile estimations. In particular, in our baseline model of the first stage of our GaR model, IGAE lags, nominal exchange rate, inflation, interest rate and US industrial production index are included, since they are significant determinants of economic activity in Mexico and would also help to mitigate an endogeneity problem between MUI and IGAE in our estimates.

<sup>9</sup>Appendix C presents the results of our estimates based on the GDP of Mexico. Our main conclusions remain unchanged.

<sup>10</sup>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 extreme values.

Our main results suggest that a higher level of uncertainty increases the downside risks to expected growth of the Mexican economy. The estimates of the lower quantiles of the expected IGAE growth distribution show more significant variability with respect to increases in the level of uncertainty compared to the central moments and the right tail of the distribution. Furthermore, during periods of economic crisis these estimates seem particularly suitable for analyzing the probability of expected recessions in the face of significant increments in the level of uncertainty. This results are similar to the analysis of Jovanovic and Ma (2020) for the U.S. economy. These authors show that higher macroeconomic uncertainty is associated with a more spread out distribution of expected output growth while 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. In another recent paper, Gu et al. (2021) investigate the impact of economic policy uncertainty (EPU) on economic activity in China. They find that the EPU alters the skewness and kurtosis of the distribution of expected growth in China in a similar fashion to our model.

Our baseline results are robust to the addition of alternative measures of uncertainty associated with both internal and external factors and to the addition of variables that control for risk and financial conditions in Mexico. In particular, estimates remain significant when controlling for the US NFCI and the financial condition index for Mexico proposed by Carrillo and García (2021). We also find that our baseline 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 measures of risk premium. Additionally, we perform other robustness tests to determine whether our results hold up to alternative measures of economic activity. We use six indicators. On the demand side, we use gross fixed investment and private consumption. On the supply side, we use 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 formal jobs (proxied by the number of jobs affiliated to the IMSS)<sup>11</sup> 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.<sup>12</sup>

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<sup>11</sup>Instituto Mexicano del Seguro Social, the social security institute of Mexico.

<sup>12</sup>Although our estimates of the effect of the MUI on the distribution of expected growth are significant and robust, the MUI has a disadvantage related to its timeliness with respect to other measures of uncertainty, risk and volatility. In particular, the MUI shows a lag with respect to IGAE. The main reason for this lag is that some indicators used as inputs for the MUI are published with a delay. Likewise, according to Jurado (2015)



Finally, we provide a more detailed analysis of the impact of uncertainty on the distribution of economic growth during the periods of the 1994 Crisis, the Great Financial Crisis of 2008, and the COVID-19 pandemic. Our results reveal that, during periods characterized by very high levels of uncertainty such as economic crises, the estimated conditional distribution on MUI of expected output growth is more consistent with realized output growth rates, since high levels of MUI seems to exacerbate the negative bias of growth projections, making the central moments of the estimated distribution relatively optimistic with respect to the realized values.

The rest of the paper 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 IGAE growth distribution. 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 the 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 of predicting the economy's behavior at a given moment has increased, which is interpreted as an increase in the level of uncertainty. Formally, the MUI can be expressed as:

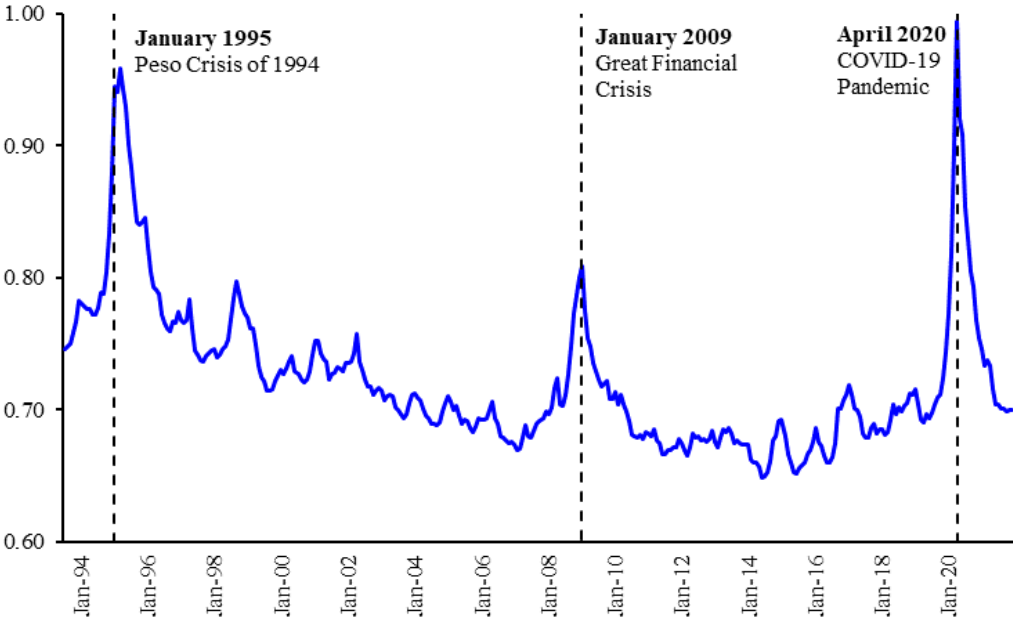
$$MUI_t^h = \frac{1}{N} \sum_{n=1}^N U_{n,t}^h \quad (1)$$

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methodology, at least one observation of the sample is lost in the estimation of the forecast error of each of the variables used in calculations of the MUI. In consequence, the timeliness of estimated impact of MUI on economic activity expectations is limited. As a result, future work of this research may focus on the development of a more timely MUI that addresses this issue. In this regard, we have tested some alternatives, although in our estimates we have detected that more timely estimates of the MUI are accompanied by much greater volatility that could bias the impact of the MUI upwards on growth expectations.

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 months ahead. In the case of Mexico, the MUI is calculated from 125 monthly frequency series of economic activity, prices, and from the external sector (See Banxico (2020b)).

Figure 1: Macroeconomic Uncertainty Index for Mexico ( $h = 1$ )  
Jul-93 - Dec-21



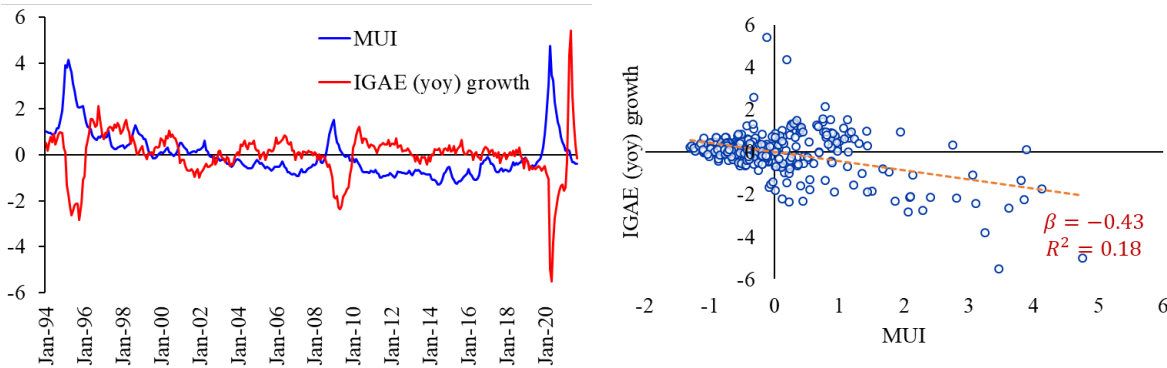
Source: Own elaboration.

For our estimates, along the paper, we consider a sample from July 1993 to December 2021, the same estimation period for the MUI with one month ahead of forecast (i.e.,  $h=1$ ).<sup>13</sup> Significant increases in the MUI are related to economic or geopolitical events that are commonly associated with an increase in the level of uncertainty. For example, the 1994 and 2008 crises are associated with environments of high uncertainty. After achieving a low point, the index trended upward, between 2015 and 2019, due to the increased uncertainty

<sup>13</sup>Our results are robust to changes in the MUI specification for 3 and 12 months ahead of forecast periods. In this regard, it stands out that the MUI tends to be an unconditional mean in the face of longer forecast horizons because 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 of greatest magnitude and persistence of uncertainty. 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 (i.e.,  $h = 1$ ).

caused by the significant drops in oil prices, the beginning of the renegotiation process of NAFTA, and electoral processes both in Mexico and the U.S. (see Figure 1). More recently, since the beginning of 2020, a sharp increase in the level of uncertainty associated with the COVID-19 Pandemic was 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 reopening of the economy and mitigation of the health crises, remained relatively high.

Figure 2: IGAE (yoy) growth and Macroeconomic Uncertainty Index for Mexico  
Apr-94 - Dec-21



Source: Own elaboration.

Notes: To facilitate comparison, both series are standardized.

As shown in Figure 2, sharp drops in economic growth are generally accompanied by high levels of macroeconomic uncertainty. 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.<sup>14</sup>

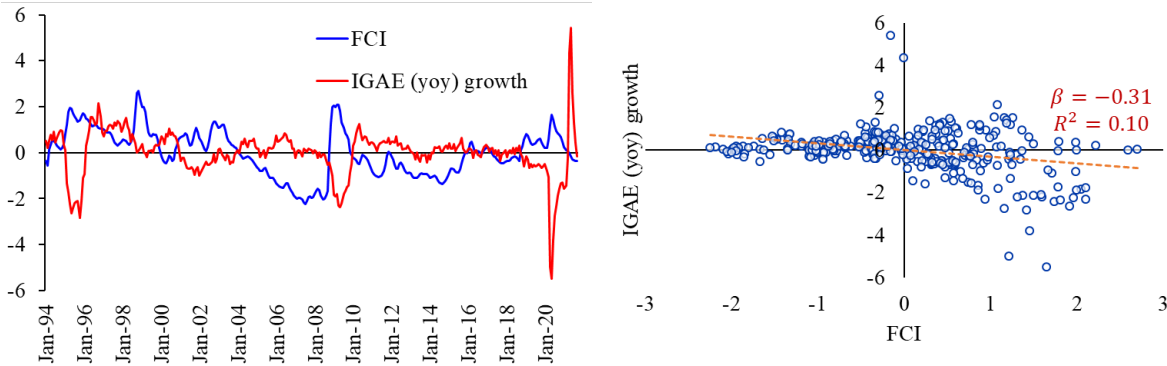
In this regard, several studies have analyzed the impact of uncertainty on growth through Vector Autoregressive (VAR) models (see Baker et al. (2016), Baker et al. (2020), Bloom (2009), Bonciani and Jason (2019), and ECB (2016), Gieseck and Rujin (2020)). This type of analysis combines real, nominal, and financial variables. These indicators are related to the level of economic activity, financial conditions, the level of uncertainty, and exposure of

<sup>14</sup>A possible objection is that this correlation could be due to the inclusion of the IGAE as one of the indicators for constructing 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 the relative weight of the IGAE is very small. On the other hand, the MUI is constructed as a weighted average of each of the series' forecast errors, so this indicator bears little relation to the level of growth.

the economy to risk. Financial conditions could also be relevant to analyze the negative bias of growth expectations (Adrian et al. (2019) and Banxico (2019, 2020a)).

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).<sup>15</sup> These authors analyze the response of several economic activity indicators to a shock in financial conditions. According to their estimates, economic activity declines in a U-shape manner for about twelve months after a shock to financial conditions. Production and consumption responses are of similar magnitudes, while investment falls to a greater extent.

Figure 3: IGAE (yoy) growth and Financial Conditions Index for Mexico  
Apr-94 - Dec-21



Source: Own elaboration.

Notes: To facilitate comparison, both series are standardized.

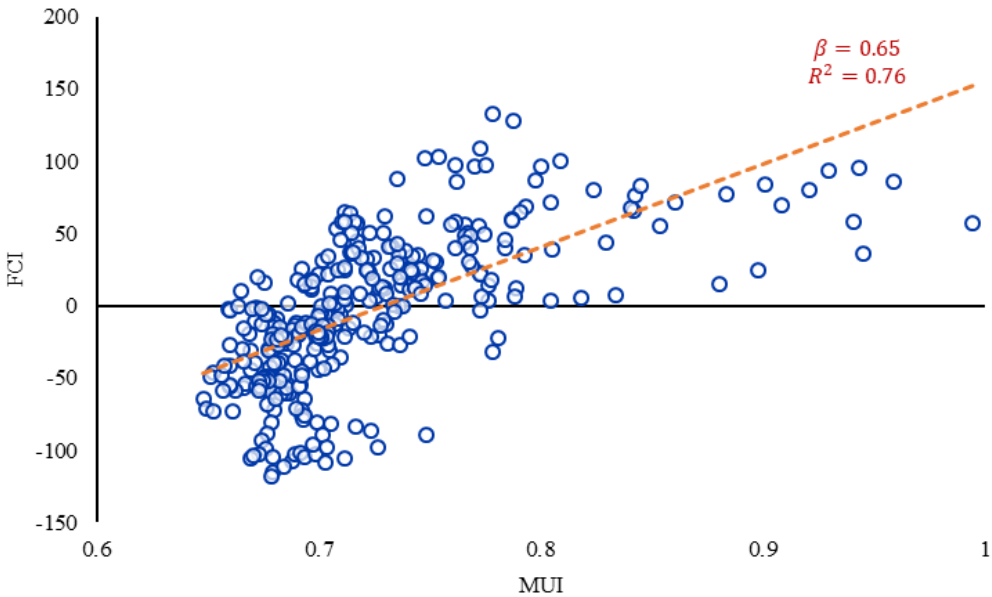
As previously observed in the case of the MUI, the FCI and economic activity in Mexico measured as the annual growth rate of IGAE also show a strong negative correlation<sup>16</sup> (see

<sup>15</sup>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 unobserved values and an unbalanced sample for all variables included. These variables are divided into seven categories: currencies, stocks, debt, uncertainty, country risk, commodity prices, and economic activity.

<sup>16</sup>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 analyses a Financial Condition Index provided by the 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

Figure 3). In addition, it is also observed an important positive relationship between the MUI and the FCI (see Figure 4). In this regard, it could possible that a tightening of financial conditions will be simply a reflection of an increase in the level of uncertainty. For instance, in environments of greater uncertainty, firms and households could face more restrictive credit and liquidity conditions associated with a greater aversion of banks to grant loans and higher costs of credit access.<sup>17</sup>

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



Source: Own elaboration.

To further study the relationship between growth, and uncertainty 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.<sup>18</sup> The shocks of the model are identified through a Cholesky identification. The VAR is estimated for a sample from July 1993 to

the annual inflation rate, finding similar results.

<sup>17</sup>The Granger causality test with three lags reveals a significant relationship. MUI is found to cause FCI (p-value = 0.00), while the influence of FCI on MUI is not as strong (p-value = 0.07) at the 0.05 significance level.

<sup>18</sup>In a related analysis, Banxico (2019) also analyzes the effect of uncertainty on consumption and investment in Mexico by estimating two VAR models, one for consumption and the other for investment.

December 2021 for ten endogenous variables in the following order: the U.S. Industrial production index (IPUS), the MUI, the FCI, the Nominal Exchange (NER), the IGAE, the Monthly Indicator of Private Consumption (PCI), the Monthly Indicator of Gross Fixed Investment (GFI), the consumer price index in Mexico (INPC) and the CETES rate of government securities (CETES).<sup>19</sup> The ordering of endogenous variables for the Cholesky identification implies that the IPUS is the most exogenous variable in the model since Mexico is considered a small open economy dependent on U.S. economic activity. In addition, we assume that the uncertainty measured by the MUI is affected contemporaneously by shocks to the IPUS but not by shocks to the other macroeconomic variables included in the analysis.<sup>20</sup> This identification strategy is in line with recent literature about the impact of uncertainty shocks on economic activity that show that macroeconomic uncertainty can be considered an exogenous source of business cycle fluctuations (for more details, see Bonciani and Jason (2019)). All variables are included in annual growth rates, except CETES, FCI, and MUI. The VAR is estimated for three lags to identify the impact of uncertainty shocks on the endogenous variables in the short term, and restrict the number of coefficients to be estimated. The IRF and FEVD are calculated for a horizon of three years ahead (i.e., 36 months).

The impulse-response functions 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.<sup>21</sup> In particular, the effect of one standard deviation (sd) shock on uncertainty has a negative effect on IGAE growth of above 0.5 sd. It remains statistically different from zero for about 11 months. In Figure 5, we present the IRF of the model's endogenous variables after a MUI shock. The direction in which the variables

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<sup>19</sup>Regarding the sources of the data, IGAE, PCI, GFI and INPC are taken from the Economic Information Bank from INEGI; NER and CETES are taken from the Economic Information System from the Bank of Mexico; the IPUS is taken from the Federal Reserve Bank of St. Louis. Finally, the MUI and the FCI are provided by the Bank of Mexico. All variables are in percentage annual growth rate variation, with the exception of MUI, FCI, and CETES and seasonal adjusted with the exception of NER, INPC and CETES.

<sup>20</sup>With the order of identification of the variables, we assume the MUI is relatively more exogenous than the FCI in the sense that shocks to the MUI affect the FCI contemporaneously, but shocks to the FCI do not affect the MUI contemporaneously. Clearly, this assumption is restrictive, and it could be suggested that an order in which it is assumed that financial conditions are more exogenous than uncertainty is more 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.

<sup>21</sup>We did not find an 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 from the mean.

respond is consistent with the exercise hypothesis: For example, in the face of shocks from uncertainty in Mexico 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 to a greater extent. The latter results are consistent with those found by Banxico (2020a) and Bonciani and Jason (2019).<sup>22</sup>

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 can be attributed to the level of uncertainty in Mexico, highlighting the relatively low contribution of financial conditions.<sup>23</sup> 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 U.S. economy. Likewise, for the case of Mexico, Banxico (2019) analyzes the impact of MUI on investment and consumption, finding similar results.<sup>24</sup>

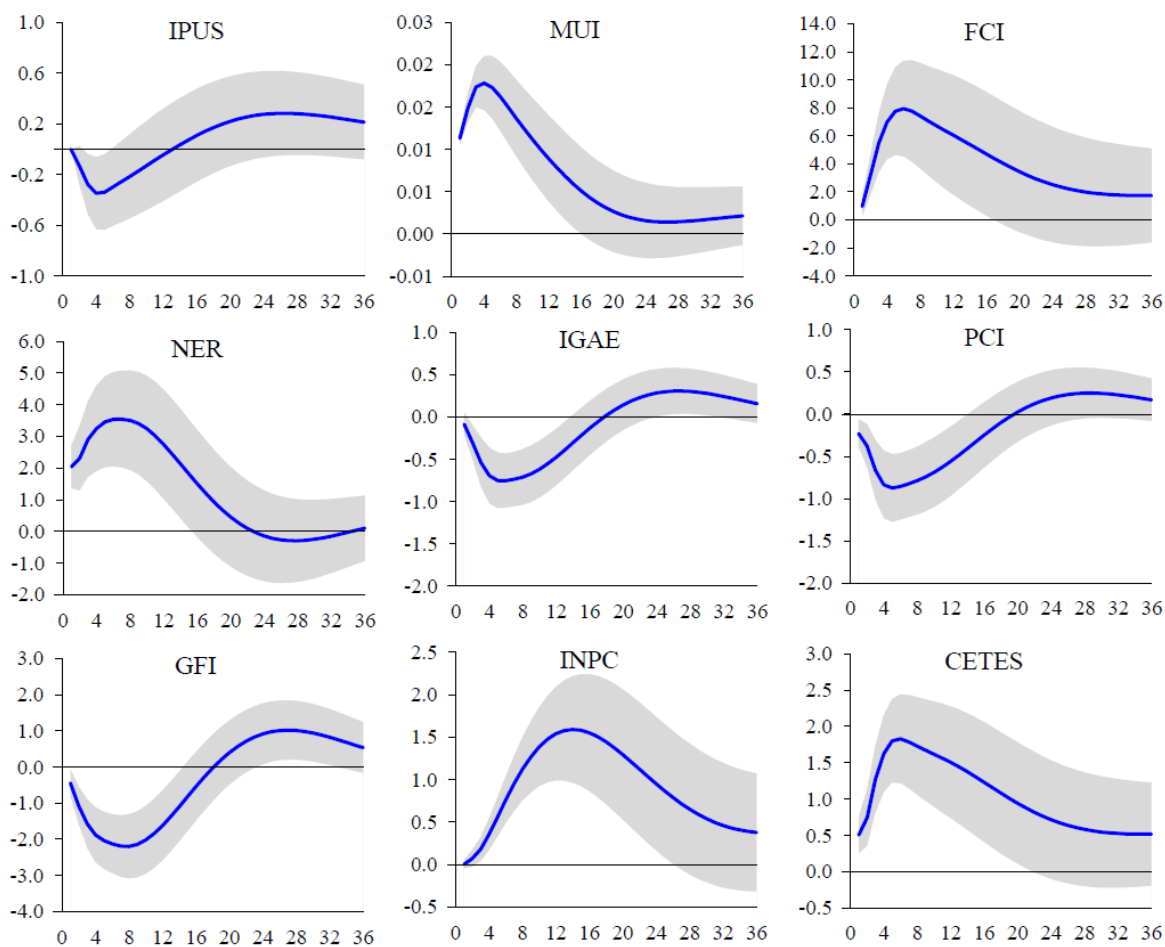
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<sup>22</sup>By including the period corresponding to the COVID-19 pandemic in the sample, SVAR estimated coefficients could be biased. To determine the magnitude of the possible bias, an additional exercise is carried out with a sample from July 1993 to December 2019. The results of the estimates are similar, although the impacts of the shocks of uncertainty on endogenous variables are generally of smaller magnitude. In this sense, the impact of uncertainty shocks is overestimated by including the pandemic period. However, this is reasonable given the enormous magnitude of the shocks observed during this period. In addition, it could also be argued that the inclusion of the sample before 2001 could bias the SVAR coefficients due to the structural change implied by the change in the exchange rate regime and monetary policy regime observed during that period. However, since our objective is to identify uncertainty shocks, not exchange rate or monetary policy shocks, we consider including the sample before 2001 appropriate. Likewise, given the large number of parameters estimated in the model, we also consider it appropriate to include said subsample to have greater freedom in the estimation.

<sup>23</sup>This result also holds under Cholesky's alternative identification, where uncertainty is considered relatively more exogenous than the FCI.

<sup>24</sup>However, unlike the previous approaches, in our analysis, we also control for financial conditions in Mexico 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  
Apr-94 - Dec-21

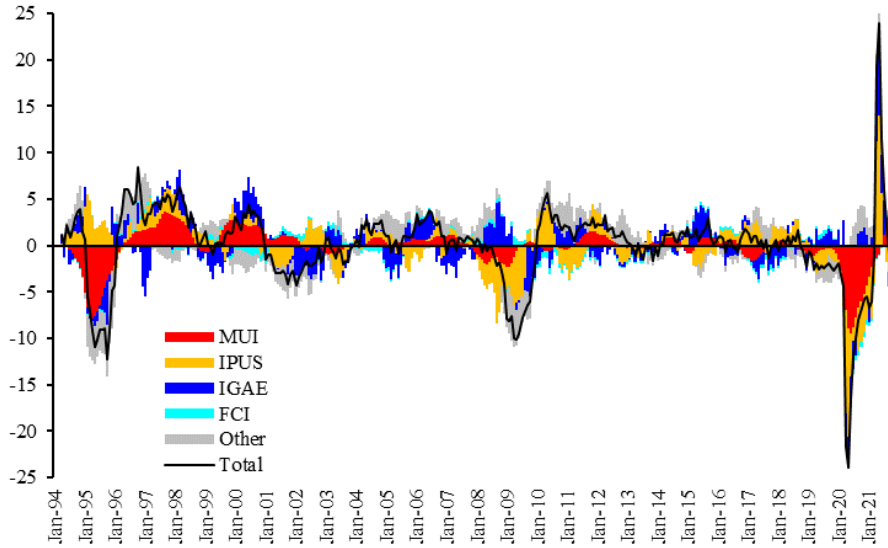


Source: Own elaboration.

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



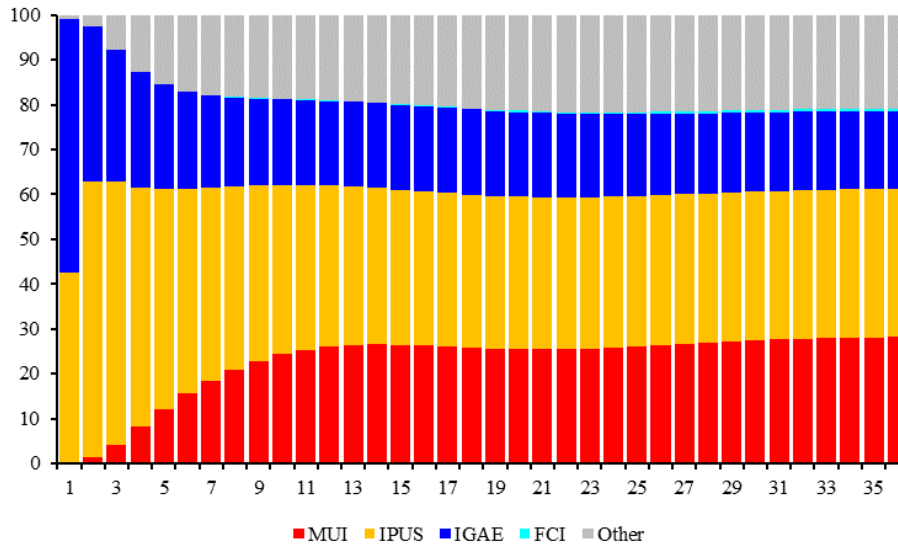
Figure 6: Historical Decomposition of IGAE (yoy) growth  
Jan-94 - Dec-21



Source: Own elaboration.

Notes: Other is the aggregated contribution of NER, PCI, GFI, INPC, CETES.

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



Source: Own elaboration.

Notes: Other is the aggregated contribution of NER, PCI, GFI, INPC, and 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 increased bias of growth expectations, and that 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). In the first stage, a quantile regression is applied between the expected annual production growth and a set of control variables. In the second stage, the parameters of a *skewed-t* distribution of output growth are estimated based on the fitted values of the quantile regression. These estimates allow us to analyze the marginal impact of the determinants of growth along their conditional distribution for each period of the sample.

#### 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  $F: \mathfrak{R} \rightarrow [0, 1]$ , and a quantile  $\tau$ , 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:

$$F^{-1}(\tau) = \inf \{x \in \mathfrak{R}: \tau \leq F(x)\} \quad (2)$$

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

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

Where  $h$  represents the number of forecast periods ahead of growth forecast,  $T$  indicates the number of observations,  $\tau$  represents the quantile of the estimate, 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:

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

In our case,  $\hat{Q}_{y_{t+h}|x_t}(\tau | x_t) = x_t \hat{\beta}_\tau$ , for a given quantile  $\tau$ , corresponds to the linear estimate of the inverse of the discrete cumulative distribution function of IGAE annual growth rate conditional on determinants  $x_t$ .<sup>25,26</sup> 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 rates 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 it would be possible with a continuous distribution. The second part of the Adrian et al. (2019) methodology allows us to estimate a continuous growth distribution function from the quantile regression estimates in to calculate not only several measures of dispersion but also 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.

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<sup>25</sup>According to Koenker and Bassett (1978),  $\hat{Q}_{y_{t+h}|x_t}(\tau | x_t) = x_t \hat{\beta}_\tau$  is a consistent linear estimator of the quantile function  $y_{t+h}$  conditional on  $x_t$ .

<sup>26</sup>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 every 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.

### 3.1.2 Second Step of GaR Methodology

In general, from quantile regression fitted values,  $\hat{Q}_{y_{t+h}|x_t}(\tau | x_t) = x_t \hat{\beta}_\tau$ , it is possible to estimate the parameters of a continuous probability distribution function. Specifically, it is possible to choose the parameters  $\psi_{t+h}$  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,

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

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 makes it possible to analyze uncertainty's impact more appropriately 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:

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

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

According to the above, for each sample period, four parameters of the *skewed-t* distribution are estimated by maximum likelihood.<sup>27</sup> The parameter  $\mu$  determines the position;  $\sigma$  is the scale parameter;  $v$  the degrees of freedom; and  $\alpha$  the shape. These parameters characterize a continuous distribution of expected IGAE annual growth for each sample period.

In addition, it is possible to analyze the impact of uncertainty on growth expectations by fitting a continuous distribution to the quantile regression estimates. 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 by comparing those distributions.

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<sup>27</sup>All estimates of our analysis are made with the free software R, mainly the packages: `quantreg` for the quantile regressions and `ghyp` and `sn` for semiparametric estimation of the *skewed-t* probability functions.

### 3.2 Data and Benchmark Model

For the estimates of GaR methodology described in the previous section, we use the same monthly sample previously analyzed in our VAR model. As a measure of economic activity in Mexico, we use IGAE. As controls we use lags of IGAE, IPUS, INF, NER, and CETES. Following GaR methodology, we analyze the impact of the MUI on different quantiles of IGAE. Our Benchmark Model is estimated from the following equation:

$$y_{t+h}^{\tau} = \beta_0^{\tau} + \beta_1^{\tau} y_t + \beta_2^{\tau} INF_t + \beta_3^{\tau} NER_t + \beta_4^{\tau} CETES_t + \beta_5^{\tau} IPUS_t + \beta_6^{\tau} MUI_t + \varepsilon_t^{\tau} \quad (7)$$

Where  $Q_{y_{t+h}|x_t}(\tau | x_t) = y_{t+h}^{\tau}$ ,  $y_t$  is 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 superscript  $h$  indicates the forecast horizon of the quantile regression, and the superscript  $\tau$  indicates the quantile being estimated, with discrete values from 0.1 to 0.9, in 0.05 intervals. For example,  $y_{t+3}^{25}$  corresponds to the 25th quantile of the IGAE growth distribution with a three months ahead forecast horizon.

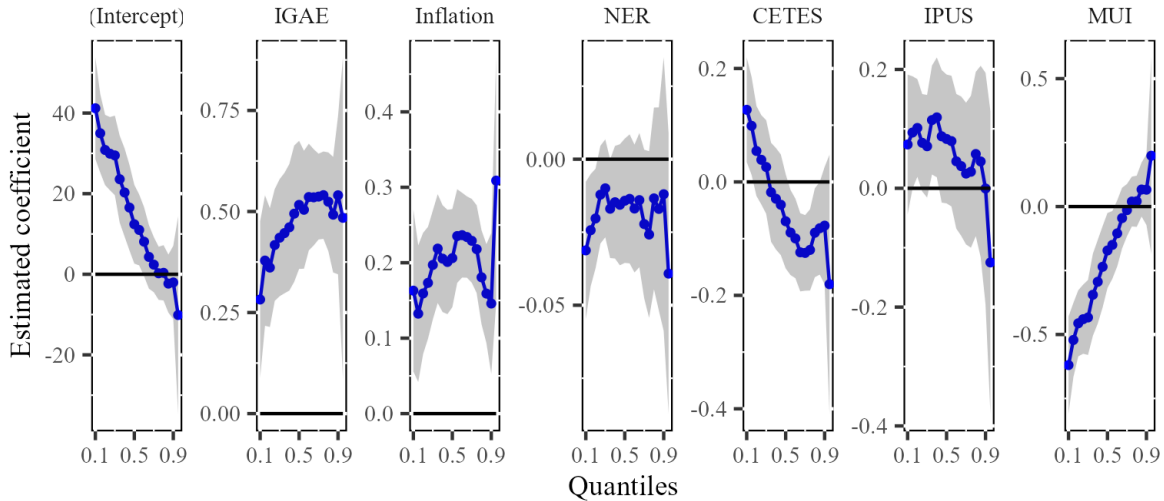
### 3.3 An Analysis of the Impact of Uncertainty on the Distribution of Growth in Mexico

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.<sup>28</sup> The results show that uncertainty has a negative and statistically significant marginal effect on the left tail of the distribution of economic growth. In contrast, 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 identifying the negative bias of growth expectations since the estimated distribution shows greater variability in the left tail associated with low growth and high uncertainty levels. In particular, according to estimated coefficients in Table 1, the marginal effect of uncertainty in the tenth quantile of estimated IGAE annual growth distribution is -0.62 percentage points (pp), higher in absolute value than the marginal effect of the MUI of -0.17 pp on the median of the distribution.

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<sup>28</sup>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 from one to 15 months.

Figure 8: Quantile Regression Coefficients for the Benchmark Model ( $h = 3$  months)  
Apr-94 - Dec-21



Source: Own elaboration.

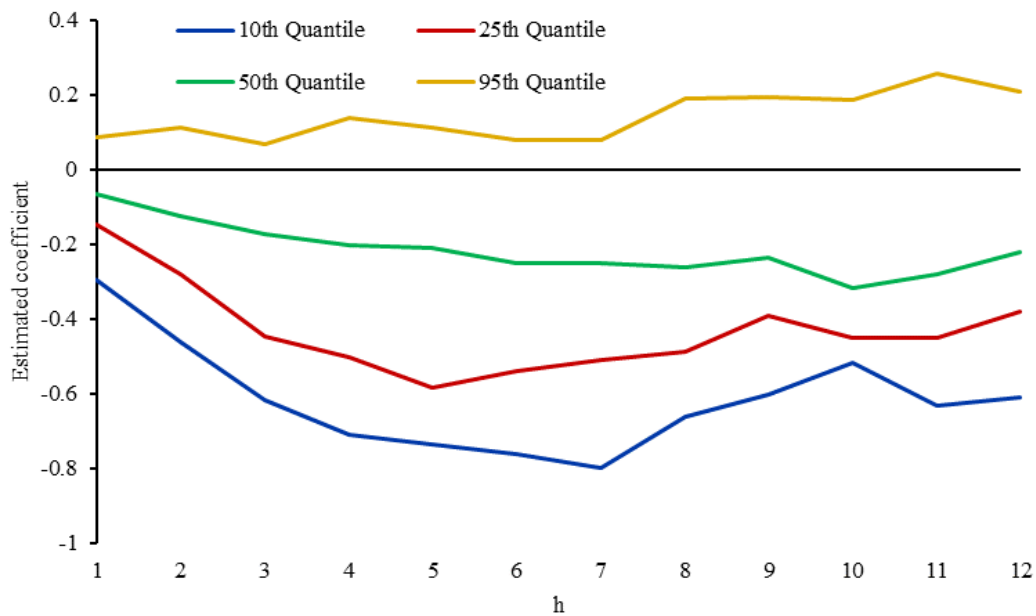
Notes: Blue lines represent estimation coefficients for each quantile. The grey band depicts 90% Confidence intervals.

Figure 9 shows estimated coefficients of the Benchmark Model for the MUI for several forecast horizons  $h$ . According to these estimates for forecast horizons of 1 to 12 months, the marginal effect of uncertainty on the expected IGAE growth is negative and of greater absolute value magnitude for quantiles of the left tail of the distribution. It should be noted that this result is similar to the one found by Jovanovic and Ma (2020) for the case of the U.S.

Based on our estimates of quantile regressions, it is also possible to analyze the dispersion and bias of the growth distribution for each sample period. In particular, it is interesting to determine the effect of uncertainty on the distribution's dispersion and median. 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 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 IGAE growth distribution. 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

Figure 9: Estimated coefficients for MUI



Source: Own elaboration.

distribution and uncertainty, which, in turn, is negatively correlated with the median. Figure 10 presents the relationship between the interquartile range<sup>29</sup> 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 analyzes have found similar results for other economies, such as the U.S. and China (see Gu et al. (2021) and Jovanovic and Ma (2020)).

<sup>29</sup>A simple measure of dispersion that can be analyzed from the estimates of the quantile regressions defined as the difference or distance between the first and third quartiles of a distribution.

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

Apr-94 - Dec-21

	10 <sup>th</sup> Quantile			25 <sup>th</sup> Quantile		
	Coef.	Lower	Upper	Coef.	Lower	Upper
<b>Intercept</b>	41.08 ***	28.40	53.77	30.42 ***	21.5	39.32
<b>IGAE</b>	0.29 ***	0.11	0.48	0.42 ***	0.3	0.56
<b>Inflation</b>	0.17 **	0.06	0.28	0.17 ***	0.1	0.24
<b>NER</b>	-0.03 **	-0.06	-0.01	-0.01	0.0	0.01
<b>CETES</b>	0.13 **	0.03	0.22	0.04	0.0	0.12
<b>IPUS</b>	0.07	-0.05	0.19	0.07	0.0	0.15
<b>MUI</b>	-0.62 ***	-0.81	-0.43	-0.45 ***	-0.58	-0.32

	50 <sup>th</sup> Quantile			90 <sup>th</sup> Quantile		
	Coef.	Lower	Upper	Coef.	Lower	Upper
<b>Intercept</b>	12.57 **	2.76	22.37	-2.03	-11.19	7.12
<b>IGAE</b>	0.52 ***	0.36	0.68	0.54 ***	0.34	0.74
<b>Inflation</b>	0.20 ***	0.14	0.27	0.15 ***	0.06	0.24
<b>NER</b>	-0.02	-0.04	0.01	-0.01	-0.06	0.03
<b>CETES</b>	-0.07	-0.15	0.02	-0.08	-0.18	0.03
<b>IPUS</b>	0.08	-0.03	0.19	0.00	-0.20	0.19
<b>MUI</b>	-0.17 *	-0.32	-0.03	0.07	-0.07	0.20

Source: Own elaboration.

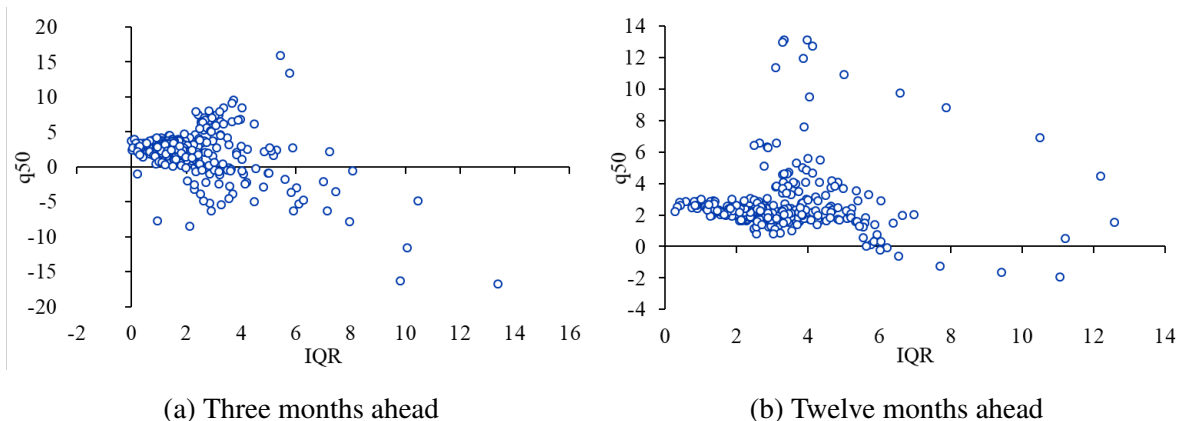
Notes “\*\*\*\*”, “\*\*\*”, “\*\*” if  $p < 0.01$ ,  $p < 0.05$ , and  $p < 0.1$ , respectively. Lower and Upper indicate the 90% confidence interval.

Another way to analyze the effect of uncertainty on the distribution of IGAE growth is by comparing 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  $\hat{Q}_{y_{t+h}|x_t}(\tau | x_t)$  from the our estimated baseline (Quantile Regression), and two versions of estimations of the cumulative *skewed* – *t* distribution. The first one is the adjusted distribution for the Benchmark Model (*skewed* – *t* With MUI), and the other one is the Benchmark Model, but eliminating from the equation the term for MUI (*skewed* – *t* Without MUI), for four periods of the sample. Through these estimates, it is possible to compare the effect of uncertainty on growth expectations during the months of April and May of 2015, the economy showed relatively low levels of uncertainty<sup>30</sup> in contrast to the months of April and

<sup>30</sup>According to the trajectory of the MUI, during April and May 2015, relatively low levels of uncertainty



Figure 10: Median and Interquartile Range Scatterplot of Quantile Regression



Source: Own elaboration.

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

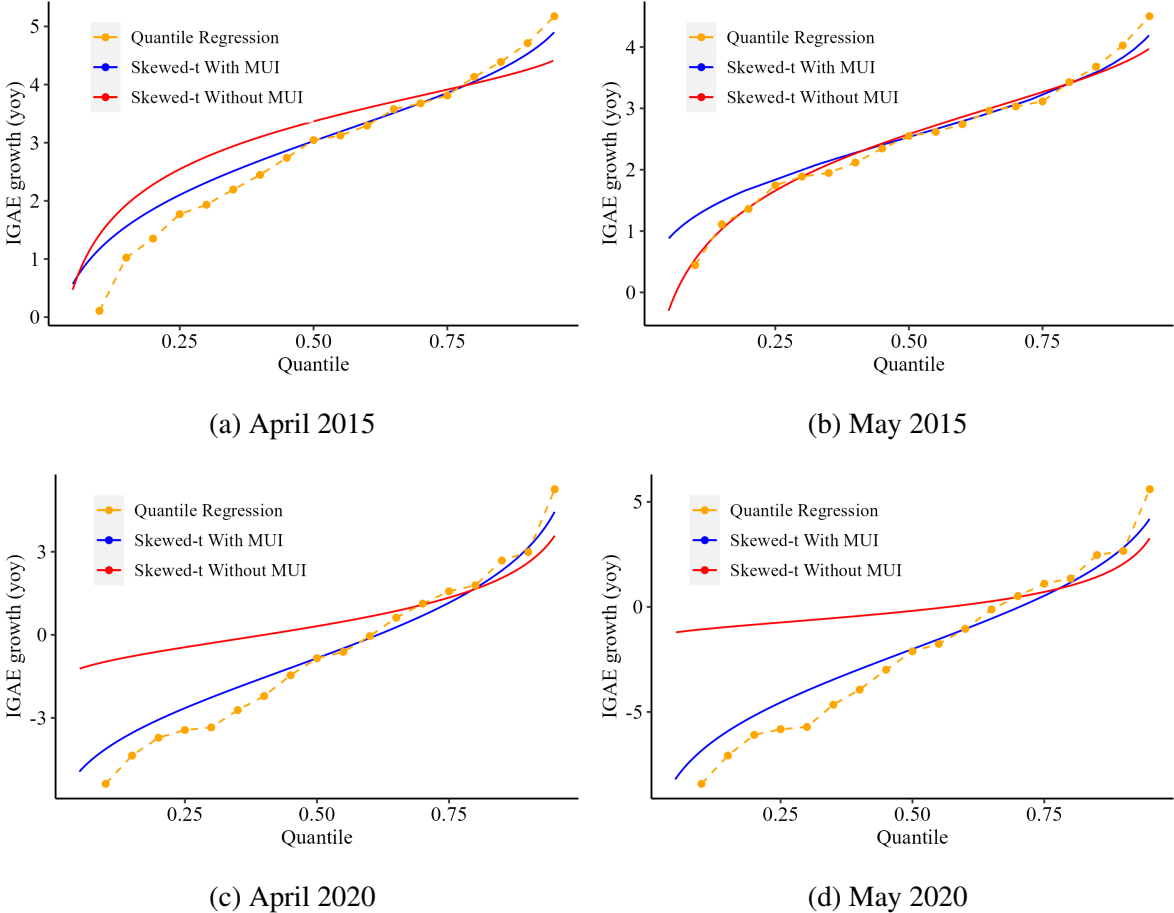
May 2020.

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*, which suggests a significant shift to the left of the expected output growth distribution, which can be interpreted as an increase in the

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 U.S. 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 from the macroeconomic uncertainty index in the Mexican economy were observed since 1993, associated with the shocks of the COVID-19 Pandemic. During that period and subsequent months, the level of uncertainty in Mexico has been relatively high despite the gradual recovery of economic activity observed since the second half of 2020.

negative bias of growth expectations during that period.

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



Source: Own elaboration.

### 3.3.1 Benchmark Model Estimated with Restricted Samples

The above evidence suggests that our results are especially sensitive to the presence of recessive periods in the sample. To assess the robustness of our results, we estimate equation 7 for two restricted samples: from April 1994 to December 2019, period that do not cover the recent COVID-19 Pandemic; and from January 2001 to September 2019, a period that does not include IGAE falls associated with the 1994 Crisis or COVID-19 Pandemic. Tables 2 and 3 show the estimates of the Benchmark Model for the sub samples. The results suggest that our model is robust to excluding 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, excluding crisis periods from the sample has an important effect on the magnitude of marginal effects of MUI, which, in general, are lower in absolute value than those obtained for the complete sample. Indeed, Table 3 shows that for the tenth quantile and the median, the unrestricted sample model estimates an impact of the MUI of -0.62 pp and -0.17 pp on IGAE growth. At the same time, this marginal effect is reduced, in absolute value, to -0.23 pp and -0.14 pp in the most restricted sample model. In this way, the previous evidence shows that the MUI is useful for identifying the negative bias of the expected growth in Mexico, even in periods of relative stability.

Table 2: Estimated Coefficients of Benchmark Model (h = 3 months; Sub-samples)  
Apr-94 - Dec-19

	10 <sup>th</sup> Quantile			25 <sup>th</sup> Quantile		
	Coef.	Lower	Upper	Coef.	Lower	Upper
<b>Intercept</b>	30.17 ***	21.88	38.46	24.38 ***	15.7	33.09
<b>IGAE</b>	0.46 ***	0.31	0.62	0.53 ***	0.4	0.65
<b>Inflation</b>	0.07	-0.03	0.17	0.19 ***	0.1	0.26
<b>NER</b>	-0.02 **	-0.04	0.00	-0.02 **	0.0	-0.01
<b>CETES</b>	0.11 **	0.02	0.20	0.02	-0.1	0.10
<b>IPUS</b>	0.10 *	0.01	0.20	0.11 **	0.0	0.19
<b>MUI</b>	-0.45 ***	-0.58	-0.33	-0.36 ***	-0.49	-0.23

	50 <sup>th</sup> Quantile			90 <sup>th</sup> Quantile		
	Coef.	Lower	Upper	Coef.	Lower	Upper
<b>Intercept</b>	16.64 ***	8.58	24.70	1.56	-12.82	15.93
<b>IGAE</b>	0.65 ***	0.55	0.76	0.60 ***	0.42	0.78
<b>Inflation</b>	0.21 ***	0.15	0.27	0.16 ***	0.07	0.24
<b>NER</b>	-0.01	-0.03	0.01	0.00	-0.04	0.05
<b>CETES</b>	-0.03	-0.10	0.04	-0.08	-0.19	0.03
<b>IPUS</b>	0.02	-0.07	0.10	0.03	-0.16	0.23
<b>MUI</b>	-0.24 ***	-0.36	-0.12	0.01	-0.21	0.23

Source: Own elaboration.

Notes “\*\*\*”, “\*\*”, “\*” if  $p < 0.01$ ,  $p < 0.05$ , and  $p < 0.1$ , respectively. Lower and Upper indicate the 90% confidence interval.

### 3.3.2 Diagnostic Tests on Estimated Quantile Regression

To determine the validity of our empirical analysis we implement two diagnostic tests on our estimated regression: Ramsey’s RESET test for model misspecification, and the Slope

Table 3: Estimated Coefficients of Benchmark Model (h = 3 months; Sub-samples)  
Jan-01 - Dec-19

	10 <sup>th</sup> Quantile			25 <sup>th</sup> Quantile		
	Coef.	Lower	Upper	Coef.	Lower	Upper
<b>Intercept</b>	16.07 **	3.97	28.18	15.19 ***	6.7	23.69
<b>IGAE</b>	0.50 ***	0.32	0.67	0.53 ***	0.4	0.65
<b>Inflation</b>	-0.27	-0.55	0.02	-0.10	-0.3	0.14
<b>NER</b>	-0.02	-0.05	0.00	-0.01	0.0	0.01
<b>CETES</b>	0.07	-0.05	0.18	0.00	-0.1	0.09
<b>IPUS</b>	0.13 **	0.03	0.22	0.15 ***	0.1	0.23
<b>MUI</b>	-0.23 **	-0.41	-0.04	-0.21 ***	-0.34	-0.08

	50 <sup>th</sup> Quantile			90 <sup>th</sup> Quantile		
	Coef.	Lower	Upper	Coef.	Lower	Upper
<b>Intercept</b>	12.49 ***	5.78	19.20	-7.67	-25.91	10.56
<b>IGAE</b>	0.44 ***	0.30	0.58	0.43 ***	0.18	0.68
<b>Inflation</b>	-0.31 **	-0.51	-0.11	-0.52 ***	-0.83	-0.21
<b>NER</b>	-0.01	-0.04	0.02	-0.05	-0.11	0.01
<b>CETES</b>	-0.05	-0.13	0.04	-0.18	-0.40	0.04
<b>IPUS</b>	0.12 **	0.03	0.21	0.04	-0.19	0.26
<b>MUI</b>	-0.14 **	-0.24	-0.04	0.20	-0.08	0.48

Source: Own elaboration.

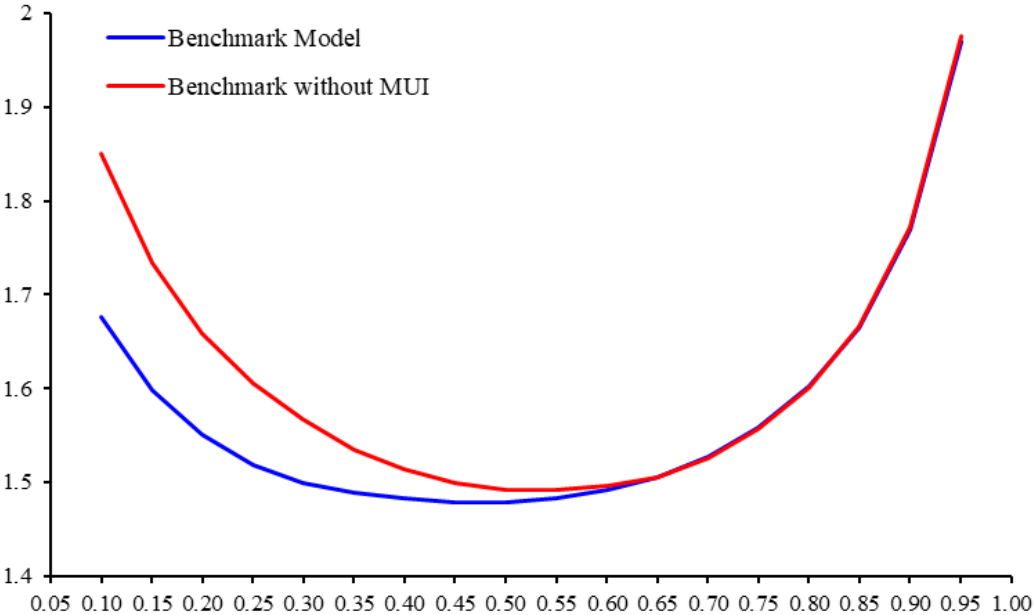
Notes “\*\*\*”, “\*\*”, “\*” if  $p < 0.01$ ,  $p < 0.05$ , and  $p < 0.1$ , respectively. Lower and Upper indicate the 90% confidence interval.

Equality test. The first test involves adding squared terms of the predicted values of the dependent variable to the original regression equation and checking whether this additional term is statistically significant. The second test is used to test the hypothesis that the slope coefficients are equal across two or more quantiles. The results of these diagnostic tests are reported in Table 4. As can be seen, our empirical estimates contain no specification errors, and there is no asymmetry in the distribution of residuals or errors around the quantiles, indicating no implications in the accuracy and reliability of the model. We thus consider our obtained quantile regression estimates to be plausible.

Additionally, we performed a Hypothesis test between MUI coefficients of the 10th and 50th quantiles. Results presented in Table 4 determine that coefficients are statistically different, thus showing evidence that uncertainty does have a differentiated effect between quantiles of the distribution of IGAE’s annual growth.

Finally, we present the Akaike Information Criterion for the Benchmark Model, and the same model but eliminating from the equation the term for MUI (Benchmark Without MUI), for each of the quantiles estimated. As can be seen in Figure 12, in the first half of quantiles the Benchmark Model consistently outperformed the modified model, as indicated by lower AIC values. This suggests that including MUI in the model is crucial for capturing the variation within the lower quantiles. However, as we move to the second half of quantiles, the AIC values between the two models become practically identical. This implies that, for higher quantiles, MUI may not contribute significantly to explaining the variation in the data.

Figure 12: Akaike Information Criterion



Source: Own elaboration.

Our results are similar to those obtained by Jovanovic and Ma (2020) and Gu et al. (2021) for the U.S. and China cases, respectively. Jovanovic and Ma (2020) propose a theoretical model in which economic growth and uncertainty 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 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

Table 4: Diagnostic Tests

Test	Statistic	P value	Decision
Ramsey RESET Test	0.18	0.67	No specification error
Symmetric Quantiles Test	8.99	0.83	Quantiles errors are symmetric
Hypothesis Test	2.55	0.03	10 <sup>th</sup> and 50 <sup>th</sup> quantiles are statistically different

Source: Own elaboration.

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 the growth distribution.

### 3.4 Relative Probability Gain and Entropy

In the previous section, we found 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 horizon of three months.<sup>31</sup> 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:

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

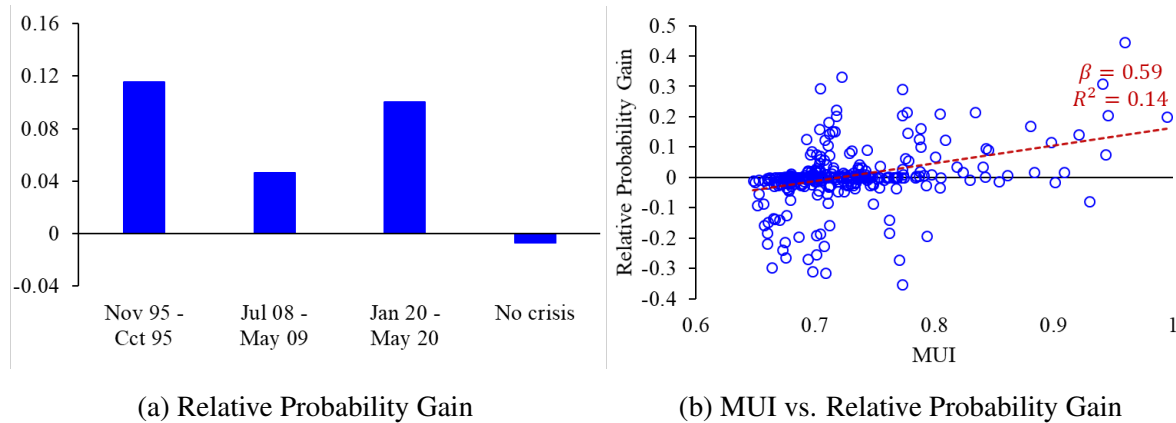
Where  $GRP_t^h(g_t)$  is the GRP in period  $t$  for a forecast horizon  $h$  and a reference growth

<sup>31</sup>It should be noted that similar results are observed for forecast horizons of one, six and twelve months.

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  $g_t$  y  $G_{IGAE}^h(y_t; X_{t-h})$  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.<sup>32</sup> Figure 13 presents the results of this exercise. The estimates suggest a significant GRP for the 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 between the GRP and the MUI stands out. Intuitively, given that the MUI significantly contributes to identify the negative bias of growth expectations, obtaining a higher GRP in the face of higher levels of uncertainty in the economy is reasonable.

Figure 13: Relative Probability Gain and MUI



Source: Own elaboration.

<sup>32</sup>Thus, for the 1994 Crisis the period from Nov-1994 to Oct.-1995 is considered, for the 2008 Financial Crisis the period from Jul.-2008 to May-2009 and for the COVID-19 Pandemic 19 the period from Jan.-2020 to May.-2020. The rest of the sample is considered a whole period without crisis, for which the average GRP is also calculated.

Relative entropy is a complementary and related measure to the GRP to analyze the risk of growth expectations. 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 concerning 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  $E_{t,h}^I$  and the upper  $E_{t,h}^S$  relative entropies in period  $t$  for estimates with forecast horizon  $h$  are define as:

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

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

Where,  $\hat{g}_h(y | x_t)$  is the adjusted density function *skewed – t without MUI*;  $\hat{f}_h(y | x_t, MUI_t)$  is the adjusted density *skewed – t with MUI*; and  $\hat{F}_h^{-1}(0.5 | x_t, MUI_t)$  is the median of function  $\hat{f}_h(y | x_t, MUI_t)$ .

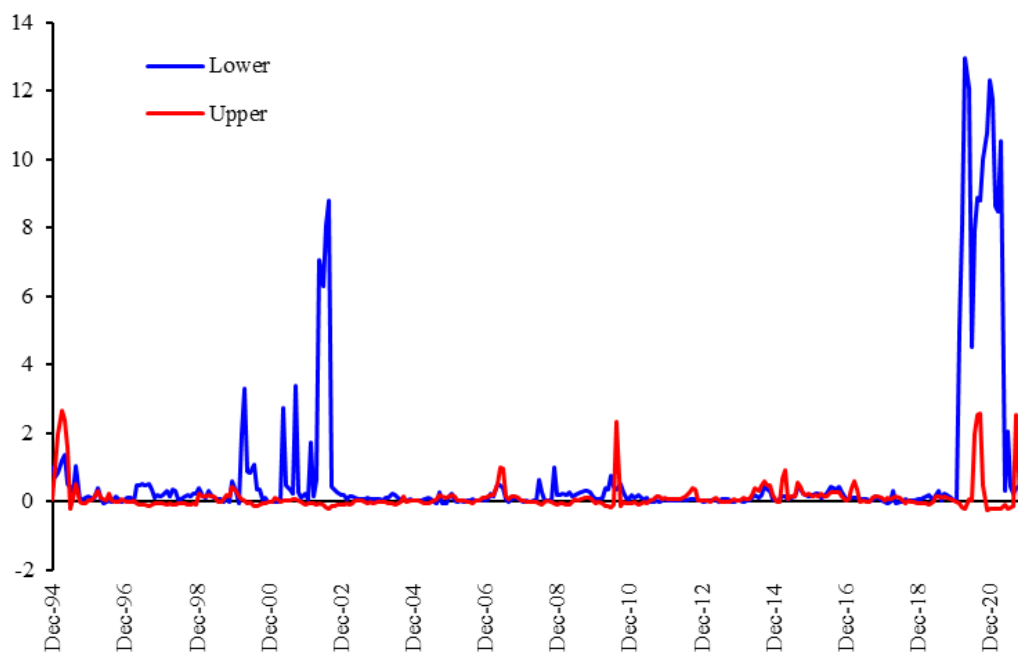
Consistent with our calculations (see Figure 14), this measure of expected growth vulnerability shows considerable downside risks to growth during the 1994 Crisis and the COVID-19 Pandemic. Downside risks seem relatively more persistent during the COVID-19 Pandemic.<sup>33</sup> Our estimates did not 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

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<sup>33</sup>Upper relative entropy estimates show relatively high levels during the 1994 Crisis. 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. In contrast, 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 extreme positive values of growth due to the high dispersion of conditional distribution in MUI.



Figure 14: Relative Entropy Index



Source: Own elaboration.

with the 1994 Crisis 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 foundations and concerning financial regulation standards that could have caused the financial shocks during this period to have a more limited impact on the real economy.

### 3.5 Robustness Analysis

Our results show significant evidence of the impact of uncertainty on the distribution of expected IGAE growth in Mexico. However, in addition to the MUI, other measures related to financial conditions, latent risk in the economy, and uncertainty are omitted from the analysis. They could be strongly correlated with the MUI. 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.

There is some evidence in the case of Mexico that financial conditions could impact the performance of economic activity. Financial conditions indices have proven to be useful tools for analyzing the economy's performance 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)).<sup>34</sup>

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

$$y_{t+h}^{\tau} = \beta_0^{\tau} + \beta_1^{\tau} y_t + \beta_2^{\tau} INF_t + \beta_3^{\tau} NER_t + \beta_4^{\tau} CETES_t + \beta_5^{\tau} IPUS_t + \beta_6^{\tau} MUI_t + \theta_{\tau} FCI_t + \varepsilon_t^{\tau} \quad (11)$$

Estimates of equation 11 show that once we control for uncertainty through the MUI, the FCI does 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 5). 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 expected economic growth in Mexico, even controlling for the state of financial conditions and other determinants of growth.

The previous result is interesting due to the contrast with Adrian et al. (2019) for the case of the U.S. 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. The preceding could be associated with characteristics of the Mexican economy, such as greater risk exposure and volatility of the financial system compared to that of developed countries.

In addition, we evaluate the validity of our results, including other indicators closely

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<sup>34</sup>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 5: Estimated Coefficients of Benchmark Model with FCI (h = 3 months)

Apr-94 - Dec-21

	10 <sup>th</sup> Quantile			25 <sup>th</sup> Quantile		
	Coef.	Lower	Upper	Coef.	Lower	Upper
<b>Intercept</b>	41.74 ***	29.04	54.44	30.42 ***	21.1	39.78
<b>IGAE</b>	0.31 ***	0.12	0.50	0.42 ***	0.3	0.56
<b>Inflation</b>	0.16 **	0.05	0.26	0.17 ***	0.1	0.25
<b>NER</b>	-0.03 *	-0.05	0.00	-0.01	0.0	0.01
<b>CETES</b>	0.12 **	0.03	0.22	0.04	0.0	0.12
<b>IPUS</b>	0.07	-0.06	0.19	0.07	0.0	0.15
<b>MUI</b>	-0.63 ***	-0.82	-0.44	-0.45 ***	-0.6	-0.31
<b>FCI</b>	0.00	0.00	0.01	0.00	0.00	0.01

	50 <sup>th</sup> Quantile			90 <sup>th</sup> Quantile		
	Coef.	Lower	Upper	Coef.	Lower	Upper
<b>Intercept</b>	12.37 *	0.94	23.80	-1.23	-10.83	8.36
<b>IGAE</b>	0.51 ***	0.36	0.67	0.51 ***	0.33	0.70
<b>Inflation</b>	0.21 ***	0.14	0.28	0.14 **	0.05	0.23
<b>NER</b>	-0.01	-0.04	0.01	-0.01	-0.06	0.04
<b>CETES</b>	-0.07	-0.16	0.01	-0.06	-0.16	0.04
<b>IPUS</b>	0.08	-0.02	0.19	0.01	-0.18	0.20
<b>MUI</b>	-0.17 *	-0.34	0.00	0.05	-0.09	0.20
<b>FCI</b>	0.00	0.00	0.00	0.00	-0.01	0.01

Source: Own elaboration.

Notes “\*\*\*”, “\*\*”, “\*” if  $p < 0.01$ ,  $p < 0.05$ , and  $p < 0.1$ , respectively. Lower and Upper indicate the 90% confidence interval.

related to the financial system and other measures of uncertainty 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 U.S. but regionally, as well as the EPU for Mexico, for the U.S. and at a global level to have measures 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 does 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) for the case of China because the EPU of Mexico does not turn out to be statistically significant once the MUI is included 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 real exchange rate<sup>35</sup> and the risk premium defined as the difference between the funds rate U.S. 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 expected IGAE growth. This result suggests that the MUI and exchange rate depreciation could be complementary to analyze the negative bias of economic growth projections in Mexico.

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

As an additional robustness exercise, we present a second block of estimates in which, instead of IGAE, we consider the following 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).<sup>36</sup> Our results show that the effect of uncertainty on the distribution of expected growth is robust to using the previous 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 economy's future performance and, therefore, directly affects the expected returns on investment. Our estimates suggest that annual investment growth is much more sensitive to changes in 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, an exercise was also carried out with quarterly frequency data using Mexico's

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<sup>35</sup>The Benchmark Model includes annual percentage growth rates for the nominal exchange rate, to assess the impact of an annual depreciation/appreciation of exchange rate on expected growth.

<sup>36</sup>All alternative indicators of economic activity are included in the Benchmark Model as annual percentage growth rates except employment rate that was included in annual variation.

GDP to measure 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 could 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 identifying of the negative bias of expected growth in Mexico.<sup>37</sup>

## **4 Analysis of Uncertainty during some Great Economic Crises in Mexico**

In this section, we present a brief analysis of uncertainty and its effects on growth during the most significant crises in the sample: the 1994 Crisis, 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 for two 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, they have in common that the evolution of each of these periods was (and has been, in the case of the COVID-19 Pandemic) characterized by high levels of uncertainty.

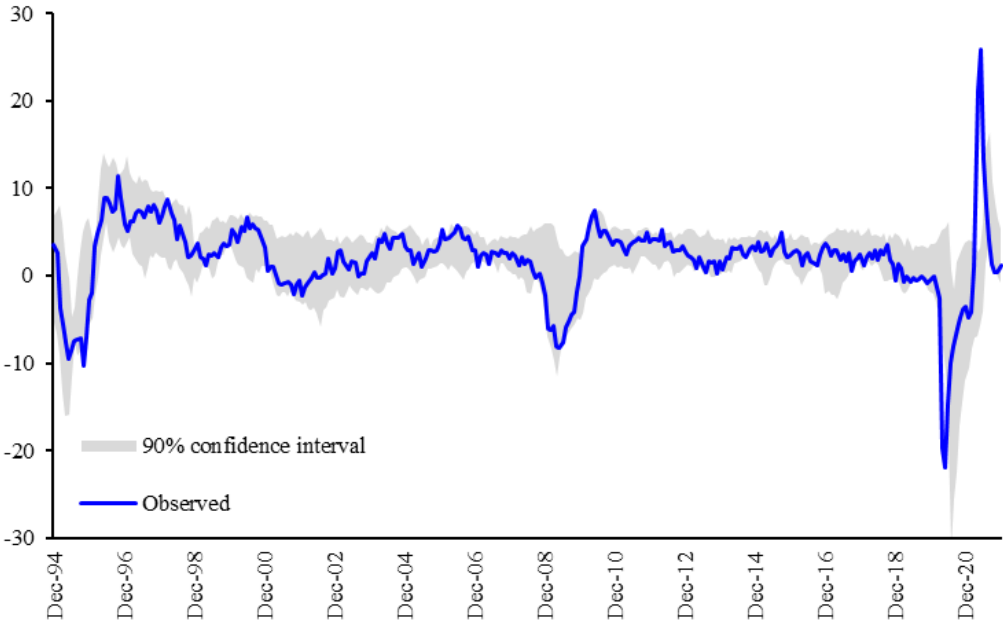
Indeed, as mentioned above, MUI estimates identify periods of economic crisis as those in which the highest levels of uncertainty have been observed (see figure 2). Furthermore, our estimates suggest that, during periods of deep recessions, the observed growth of economic activity is more similar to estimates of the lower quantiles of the expected growth distribution than those levels of central moments such as the median. In other words, expected output falls

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<sup>37</sup>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 an 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.

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 observed growth levels (Figure 15).

Figure 15: IGAE (yoy) growth Estimated Conditional Distribution



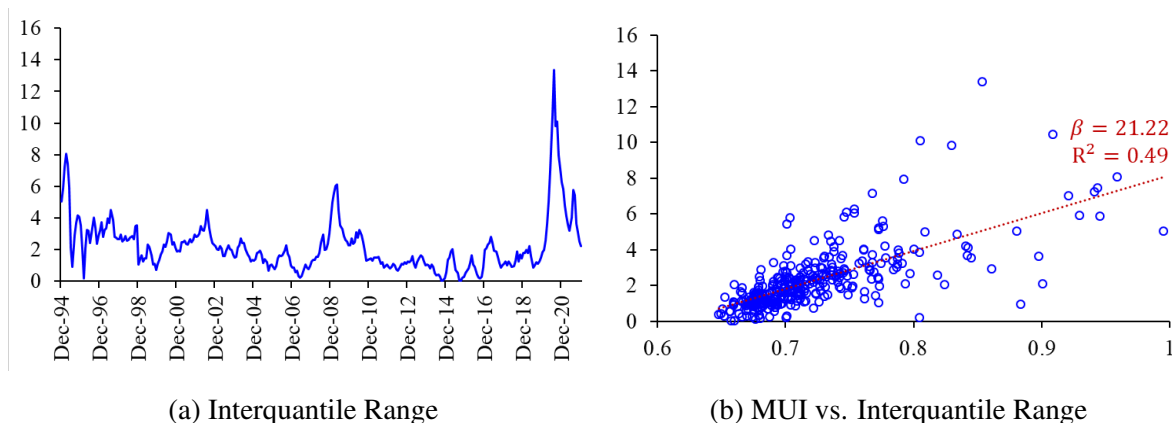
Source: Own elaboration.

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

Our results also imply that estimates of the distribution of expected economic growth during recessions are accompanied by greater dispersion. Figure 16 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 occurred during the 1994 Crisis, followed by the Great Financial Crisis 2008. This greater dispersion of growth expectations can be associated with higher levels of uncertainty. In particular, when comparing this measure of the 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, which implies an increase in the probability of observing especially lower

and negative growth levels in the case of recessive periods.

Figure 16: IGAE (yoy) growth Estimated Conditional Dispersion



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 to observe the effect of uncertainty on these estimates and have a clearer picture of the negative bias of growth expectations that prevailed in those periods.<sup>38</sup>

#### 4.1 1994 Crisis

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

Consistent with the environment in which the 1994 Crisis occurred, 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 June 1995, months in which the deepest drops in the product occurred. In both the quantile regressions and in the *skewed* – *t* distributions, a significant increase in the dispersion of the distribution is

<sup>38</sup>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).

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 13).

More specifically, in May 1995, the *skewed – t with MUI* distribution shows a significant bias towards negative IGAE growth rates. 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 17).<sup>39</sup> All these results indicate a significant negative bias in growth expectations during the 1994 Crisis. Furthermore, the entropy estimates presented above are consistent with a significant increase in growth vulnerability during that period (see Figure 14).

## 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 U.S., first to other industrialized countries and later to emerging economies, through two main shocks: demand and 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 preceding, along with an increase in risk aversion and a contraction in liquidity, contributed to a significant increase in uncertainty in Mexico and the rest of the world, accompanied by a deep recession at the global level. In particular, Mexico's GDP fell by nearly 8%, at annual rate, 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 18). In this sense, as we have shown previously, our estimates also show a significant increase in the dispersion of growth expectations (see Figure 16) and a GRP increase during the crisis period (see Figure 13). However, unlike the analysis of the

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<sup>39</sup>The estimates corresponding to May and June 1995, which have been omitted in the article, present a similar result, although it can be noted that, although 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 have much lower growth rates.



1994 Crisis, this negative growth bias appears to be of a lower 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 relatively minor difference between estimates of distributions of expected growth with and without MUI, compared to those calculated for the 1994 Crisis, could be due to the nature of uncertainty and the shocks that caused the fall in output. In 1994-1995, the crisis originated in strong internal imbalances and the inadequate implementation of economic policies that exacerbated the initial shock relatively quick, significantly raising uncertainty. In the case of the Great Financial Crisis 2008, the initial shock was observed in September 2008 in the U.S. 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 international 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, originated from a health emergency and not from an economic phenomenon itself, has profoundly impacted the global economy. 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 Mexico, since the beginning of 2020, in response to the COVID-19 health crisis, health authorities implemented social distancing measures and the closure of non-essential activities, emulating the responses implemented in other countries. We know that these actions have translated into shocks to the economy both on the demand and supply sides. Mexico is an open economy integrated into global value chains. Initially, the pandemic caused a lower demand for Mexican exports, as well as interruptions in the supply chains that affected the supply of certain inputs.<sup>40</sup>

The estimated probability distributions of expected growth for the month of May 2020, a 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 19), show, similarly to the cases of the 1994 Crisis and the Great Financial Crisis of 2008, an increase in the negative bias of growth expectations (see Figure 13). Likewise, our estimates of relative entropy show a very important increase in the vulnerability of growth, greater magnitude than those

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<sup>40</sup>Primarily during the pandemic, Asian economies, particularly China, implemented measures to contain contagion, and more recently, the semiconductor shortage severely impacted manufacturing.

registered during previous crises, which has decreased significantly in the last months of the sample (see Figure 14). However, unlike the estimates for the periods of the 1994 crisis 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 15).<sup>41</sup> The preceding is evidence that the period of the pandemic has been characterized by registering very atypical growth levels that highlight the difficulty of measuring its impact on economic activity.

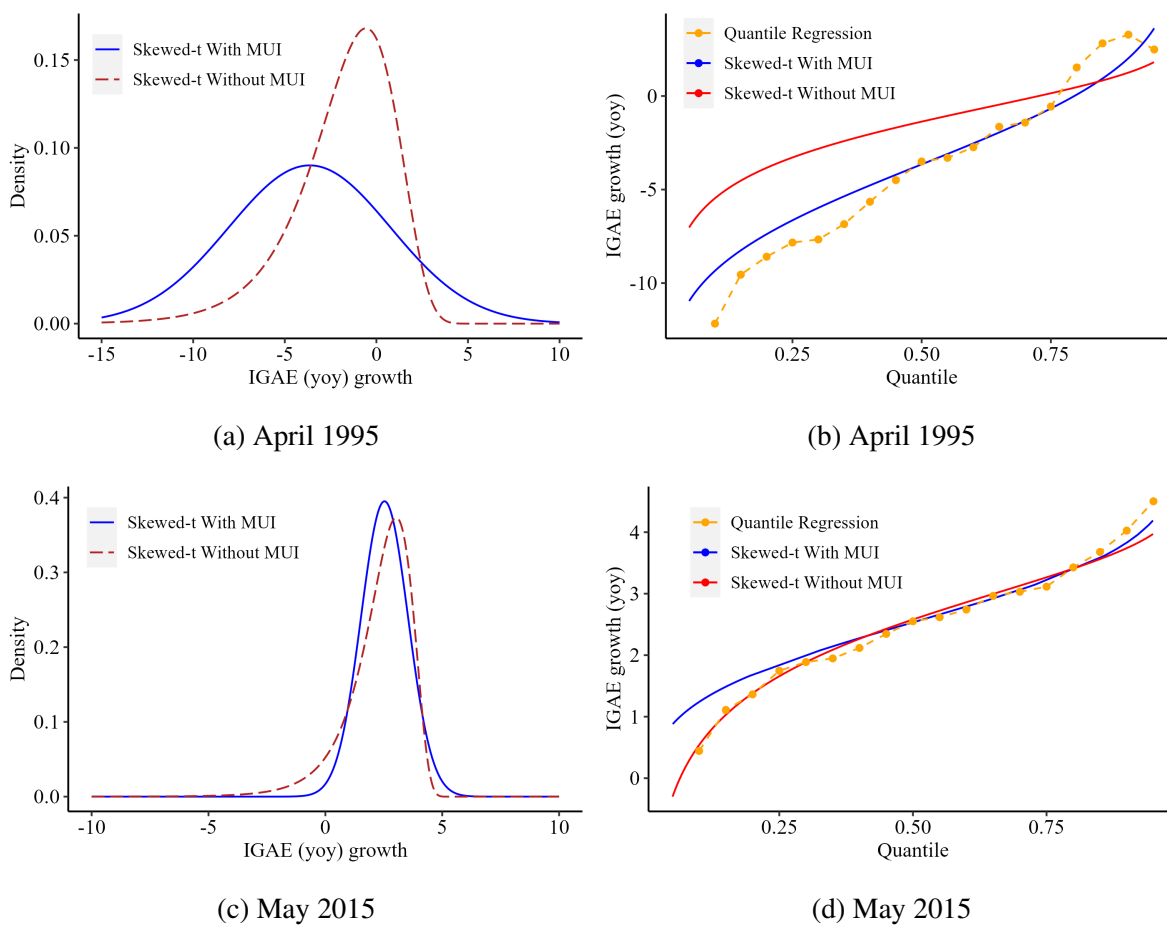
In this regard, we consider it necessary to justify, to a certain extent, why we observe a relatively important error in the adjustment of estimates of the distribution of expected growth during the COVID-19 Pandemic. In the first place, unlike previous recessive periods, this economic crisis originated mainly in non-economic conditions associated with the health emergency. This characteristic makes it difficult for policymakers to estimate the incidence of each shock. It could generate greater uncertainty associated with inadequate 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. The magnitude of its effects has been heterogeneous 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.<sup>42</sup>

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<sup>41</sup>It should be noted that this characteristic of the observed level of annual IGAE growth is maintained even considering confidence bands at 99% for estimations of the distribution

<sup>42</sup>Although our sample covers until December 2021, and variants of the coronavirus, such as Omicron, began to appear, in Mexico, in January 2022, the impact of the surge of variants of the disease 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)).

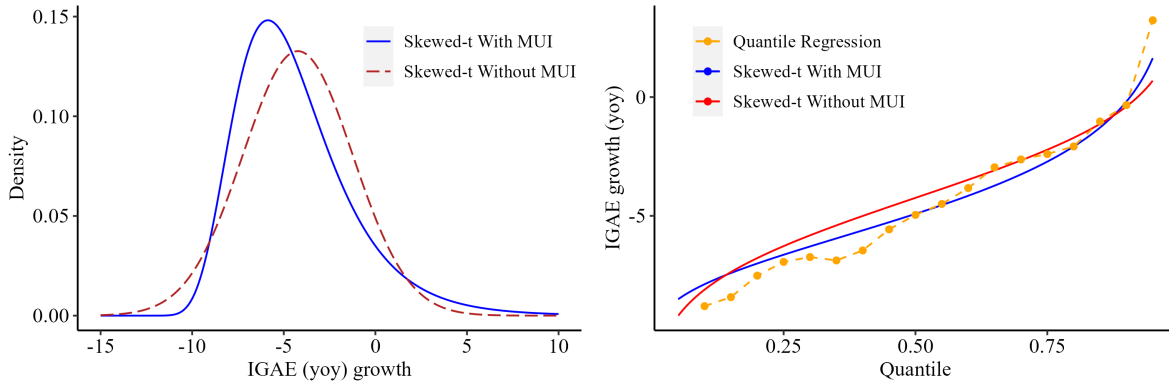
Figure 17: Probability Density Function and Cumulative Distribution Function



Source: Own elaboration.

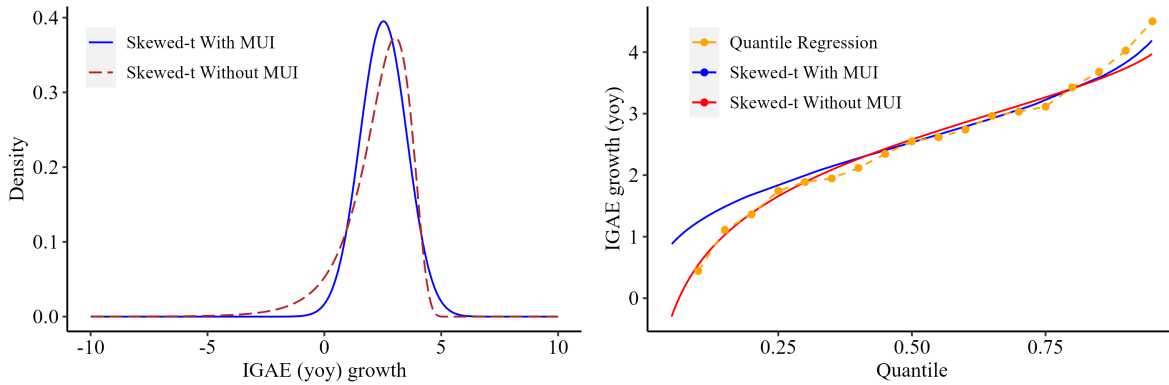
Notes: Distributions are estimated from the models with a 3-month forecast horizon. Cumulative density function plots (b and d) have the quantile on the x-axis. Therefore it should be interpreted as the probability of having a y-o-y growth less than or equal to the value on the y-axis.

Figure 18: Probability Density Function and Cumulative Distribution Function



(a) May 2009

(b) May 2009



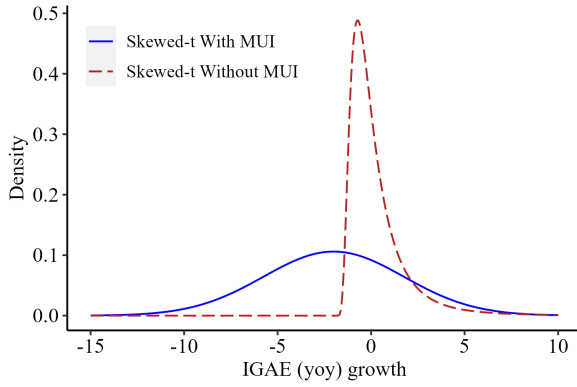
(c) May 2015

(d) May 2015

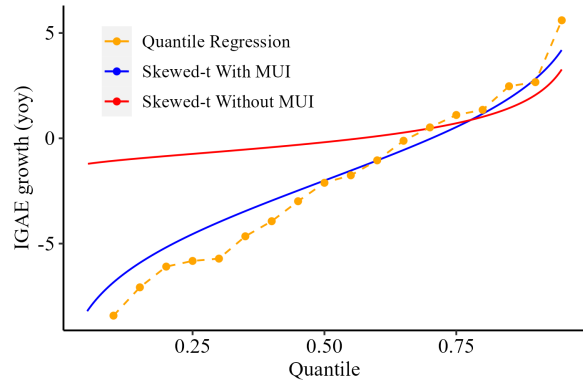
Own elaboration.

Notes: Distributions are estimated from the models with a 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.

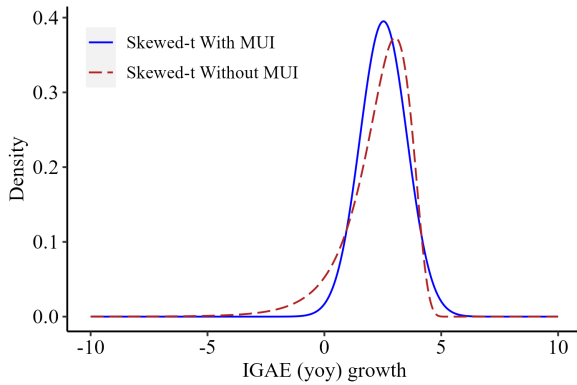
Figure 19: Probability Density Function and Cumulative Distribution Function



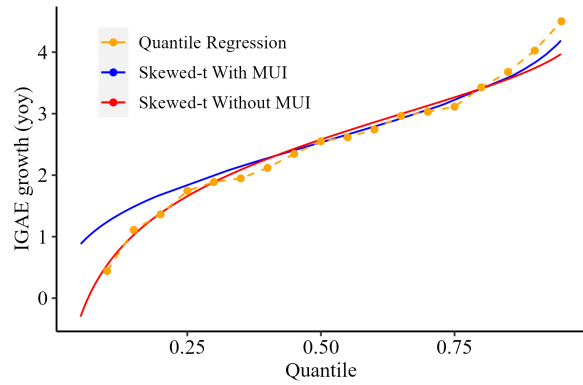
(a) May 2020



(b) May 2020



(c) May 2015



(d) May 2015

Own elaboration.

Notes: Distributions are estimated from the models with a 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.

## 5 Conclusions

The analysis of the relationship between uncertainty and expected growth is of interest both theoretically and empirically, as well as for economic policy. Policymakers need to understand the channels through which uncertainty impacts the real economy since high uncertainty is associated with growth at risk. This topic is of special interest in the current situation of the COVID-19 pandemic, a shock that has affected global economic activity, labor markets, and financial markets, generating a high degree of uncertainty about the evolution of the economy and the possible long-term consequences across countries.

In this paper, we analyzed the empirical relationship between uncertainty and growth expectations in Mexico. As a first approximation, we analyzed the impact of uncertainty on growth through the estimates of an Autoregressive Vector (VAR) of the IGAE annual growth rates, controlling for the MUI and other determinants of economic activity such as the U.S. industrial production index, exchange rate, inflation, consumption and investment, the CETES rate and financial conditions as measured by the FCI proposed by Carrillo and García (2021). This first analysis shows that uncertainty has a negative and statistically significant impact on economic growth, consumption, and investment in Mexico. In turn, we highlight that increases in uncertainty lead to tighter financial conditions. In contrast, a shock to financial conditions is not statistically different from zero on economic activity, consumption, and investment. Our results show that, when controlling for the degree of uncertainty in the economy, several measures of financial conditions do not seem to have a significant power for explaining the dynamics of economic activity in Mexico.

Although the above results provide evidence that uncertainty is an important determinant of growth, Adrian et al. (2019) argue that point forecast estimates often ignore the bias of expectations around a central scenario and may therefore be overly optimistic. We thus 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 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. The preceding implies that uncertainty significantly contributes to explain 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 1994 crises, the Great Financial Crisis of 2008, and the COVID-19 pandemic, our estimates of the expected growth distribution show a significant negative bias in growth expectations associated with the high levels of uncertainty realized during those periods. In this sense, we show that our approach of a GaR model with the MUI leads to estimate a conditional distribution of expected output growth which is more consistent with realized output growth rates, since high levels of macroeconomic uncertainty seem to exacerbate the negative bias of growth projections.

Our results are robust to the inclusion of 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 significantly affect the distribution of growth. We argue that measures of financial conditions for countries like Mexico could, in part, be a proxy for the level of uncertainty given the greater exposure to risk and volatility of the economy, so that once there is an adequate measure of the uncertainty such as the MUI, financial conditions lose explanatory power.

Finally, we study 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. Our baseline results hold for these alternative measures, although they do reveal slightly differentiated effects of uncertainty on their growth distributions. In particular, investment presented the greatest impact of uncertainty, while the employment rate registered the least impact. In this way, a relevant extension of our analysis could consist of analyzing the impact of uncertainty on the distribution of expected growth of indicators listed above and others, possibly at the sectoral level, to identify the risks to growth expectations and their relationship with uncertainty.

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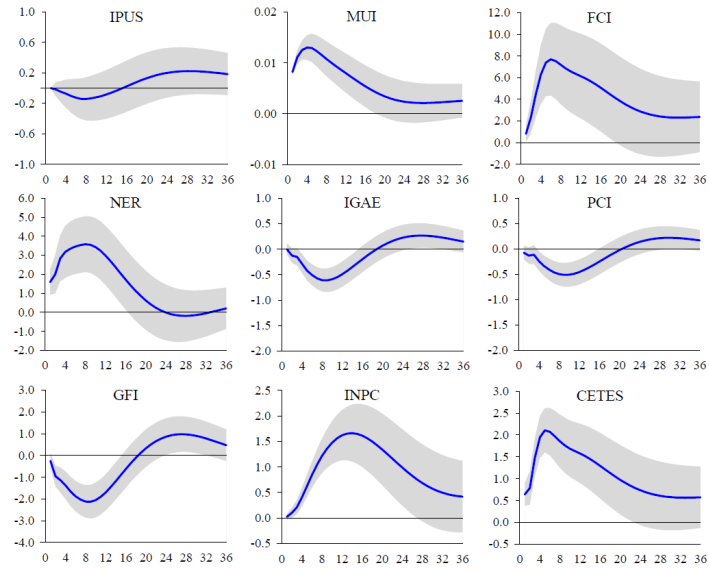
## **Appendix A    Uncertainty and Growth in Mexico through a VAR analysis**

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 IPUS, FCI, NER, PCI, GFI, INPC and CETES. All variables have a monthly frequency, MUI and FCI are provided by the Bank of Mexico; PCI and GFI are taken from the Bank of Economic Information (BIE) from INEGI; and NER, INPC and CETES from the Economic Information System of the Bank of Mexico; IPUS is provided by the Federal Reserve of Economic Data (FRED).

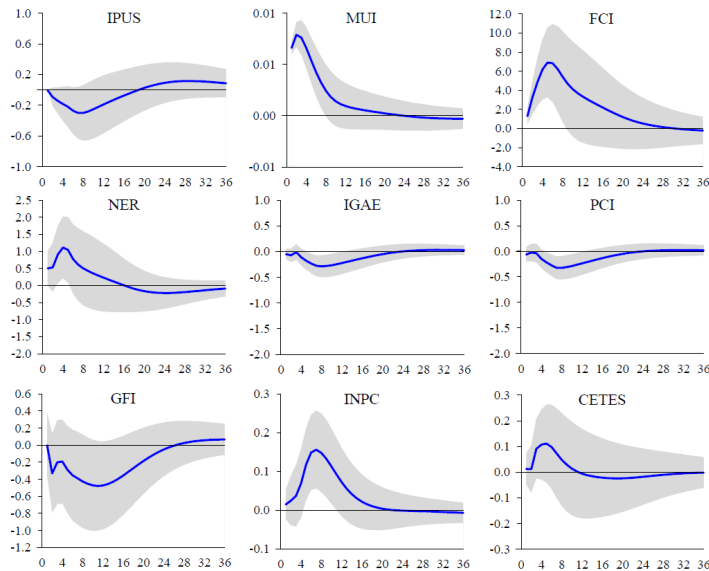
This complementary analysis is of interest, since the results of a VAR can be sensitive to changes in i) the period of estimation, and ii) the hierarchy of shocks in the Cholesky ordering (that is, the order of the variables based on their contemporary response to shocks in the errors of each variable). In this appendix IRF is presented for three alternative VAR specifications. The first couple of models were estimated with a shorter period. In the last, 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.

## A.1 VAR Results for Alternative Periods of Estimation

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



(a) Apr-94 - Dec-19.



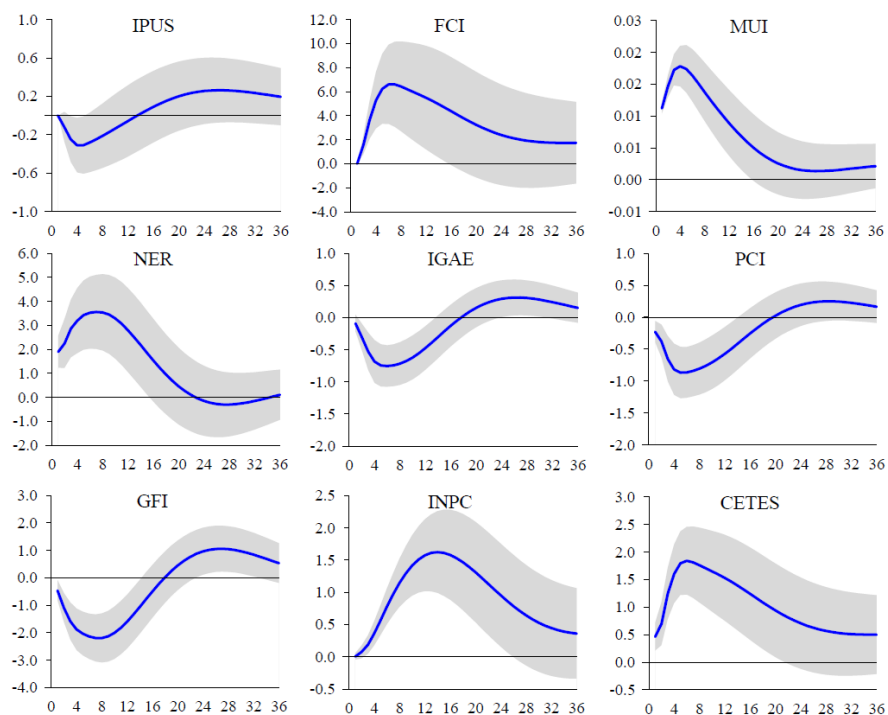
(b) Jan-01 - Dec-19.

Source: Own elaboration.

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

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

Figure 21: Response to Cholesky One S.D (d.f. adjusted) Innovations to MUI  
Apr-94 - Dec-21



(a) Impulse Response Functions

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

## 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 other variables related to the state of financial conditions, uncertainty and risk in Mexico. In particular, we estimate through a quantile regression the following equation:

$$y_{t+h}^{\tau} = \beta_0^{\tau} + \beta_1^{\tau} y_t + \beta_2^{\tau} INF_t + \beta_3^{\tau} NER_t + \beta_4^{\tau} CETES_t + \beta_5^{\tau} IPUS_t + \beta_6^{\tau} MUI_t + \rho_{\tau} Z_t + \varepsilon_t^{\tau} \quad (12)$$

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 real exchange rate (RER) and the risk premium as more traditional measures of exposure to risk and uncertainty in Mexico, respectively for each estimate. The 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 6: Estimated Coefficients of Benchmark Model with NFCI (h = 3 months)  
Apr-94 - Dec-21

	10 <sup>th</sup> Quantile			25 <sup>th</sup> Quantile		
	Coef.	Lower	Upper	Coef.	Lower	Upper
<b>Intercept</b>	41.48 ***	24.38	58.58	29.56 ***	19.1	40.02
<b>IGAE</b>	0.31 **	0.11	0.51	0.43 ***	0.3	0.57
<b>Inflation</b>	0.17 **	0.06	0.28	0.17 ***	0.1	0.24
<b>NER</b>	-0.03 **	-0.05	-0.01	-0.01	0.0	0.01
<b>CETES</b>	0.13 **	0.03	0.23	0.04	0.0	0.13
<b>IPUS</b>	0.02	-0.13	0.16	0.05	0.0	0.14
<b>MUI</b>	-0.63 ***	-0.88	-0.37	-0.44 ***	-0.6	-0.28
<b>NFCI</b>	-0.23	-1.16	0.70	-0.29	-0.86	0.28

	50 <sup>th</sup> Quantile			90 <sup>th</sup> Quantile		
	Coef.	Lower	Upper	Coef.	Lower	Upper
<b>Intercept</b>	12.07 **	3.52	20.61	-1.86	-10.98	7.26
<b>IGAE</b>	0.52 ***	0.38	0.67	0.53 ***	0.31	0.74
<b>Inflation</b>	0.22 ***	0.16	0.28	0.13 **	0.04	0.23
<b>NER</b>	-0.02	-0.04	0.00	-0.01	-0.05	0.03
<b>CETES</b>	-0.07	-0.14	0.01	-0.05	-0.16	0.05
<b>IPUS</b>	0.03	-0.08	0.14	-0.01	-0.20	0.17
<b>MUI</b>	-0.17 **	-0.30	-0.05	0.06	-0.08	0.19
<b>NFCI</b>	-1.03 ***	-1.56	-0.50	-1.24 **	-2.16	-0.33

Source: Own elaboration.

Notes “\*\*\*”, “\*\*”, “\*” if  $p < 0.01$ ,  $p < 0.05$ , and  $p < 0.1$ , respectively. Lower and Upper indicate the 90% confidence interval.

Table 7: Estimated Coefficients of Benchmark Model with EPU (h = 3 months)  
Apr-97 - Dec-21

	10 <sup>th</sup> Quantile			25 <sup>th</sup> Quantile		
	Coef.	Lower	Upper	Coef.	Lower	Upper
<b>Intercept</b>	39.24 ***	24.57	53.90	23.17 ***	13.3	33.04
<b>IGAE</b>	0.10	-0.09	0.30	0.16	0.0	0.36
<b>Inflation</b>	0.14	-0.01	0.28	0.15 **	0.1	0.25
<b>NER</b>	0.02	-0.02	0.05	0.02	0.0	0.04
<b>CETES</b>	0.09	-0.02	0.20	-0.01	-0.1	0.07
<b>IPUS</b>	0.22 **	0.05	0.38	0.28 ***	0.2	0.38
<b>MUI</b>	-0.57 ***	-0.79	-0.35	-0.32 ***	-0.5	-0.18
<b>EPU</b>	-0.01 ***	-0.01	0.00	-0.01 ***	-0.01	0.00

	50 <sup>th</sup> Quantile			90 <sup>th</sup> Quantile		
	Coef.	Lower	Upper	Coef.	Lower	Upper
<b>Intercept</b>	6.96	-1.95	15.87	-1.29	-15.75	13.17
<b>IGAE</b>	0.28 **	0.10	0.46	0.48 ***	0.26	0.71
<b>Inflation</b>	0.22 ***	0.13	0.32	0.17 **	0.03	0.31
<b>NER</b>	0.02	-0.01	0.05	-0.03	-0.08	0.02
<b>CETES</b>	-0.14 ***	-0.23	-0.06	-0.09	-0.22	0.03
<b>IPUS</b>	0.27 ***	0.15	0.40	-0.02	-0.23	0.19
<b>MUI</b>	-0.08	-0.21	0.06	0.07	-0.14	0.28
<b>EPU</b>	-0.01 ***	-0.01	0.00	0.00	-0.01	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.

Table 8: Estimated Coefficients of Benchmark Model with EPU US (h = 3 months)  
Apr-97 - Dec-21

	10 <sup>th</sup> Quantile			25 <sup>th</sup> Quantile		
	Coef.	Lower	Upper	Coef.	Lower	Upper
<b>Intercept</b>	41.18 ***	21.98	60.38	22.02 ***	11.0	33.06
<b>IGAE</b>	0.13	-0.08	0.33	0.21	0.0	0.43
<b>Inflation</b>	0.15	-0.01	0.31	0.19 ***	0.1	0.30
<b>NER</b>	0.00	-0.03	0.04	0.01	0.0	0.03
<b>CETES</b>	0.14 *	0.00	0.27	-0.03	-0.1	0.07
<b>IPUS</b>	0.14	-0.03	0.32	0.25 ***	0.1	0.37
<b>MUI</b>	-0.61 ***	-0.91	-0.31	-0.32 ***	-0.5	-0.15
<b>EPU US</b>	0.00	-0.01	0.01	0.00	-0.01	0.00

	50 <sup>th</sup> Quantile			90 <sup>th</sup> Quantile		
	Coef.	Lower	Upper	Coef.	Lower	Upper
<b>Intercept</b>	5.64	-3.53	14.82	-2.06	-17.95	13.83
<b>IGAE</b>	0.29 **	0.10	0.48	0.47 ***	0.23	0.71
<b>Inflation</b>	0.23 ***	0.14	0.32	0.16 **	0.03	0.30
<b>NER</b>	0.02	0.00	0.05	-0.04	-0.09	0.01
<b>CETES</b>	-0.15 ***	-0.23	-0.06	-0.09	-0.22	0.04
<b>IPUS</b>	0.29 ***	0.17	0.41	0.01	-0.20	0.22
<b>MUI</b>	-0.06	-0.20	0.08	0.07	-0.16	0.31
<b>EPU US</b>	0.00 *	-0.01	0.00	0.00	-0.01	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.



Table 9: Estimated Coefficients of Benchmark Model with EPU Global (h = 3 months)  
Apr-97 - Dec-21

	10 <sup>th</sup> Quantile			25 <sup>th</sup> Quantile		
	Coef.	Lower	Upper	Coef.	Lower	Upper
<b>Intercept</b>	39.45 ***	24.61	54.29	23.17 ***	13.0	33.35
<b>IGAE</b>	0.09	-0.10	0.29	0.17	0.0	0.36
<b>Inflation</b>	0.14	0.00	0.29	0.15 **	0.1	0.25
<b>NER</b>	0.02	-0.02	0.05	0.02	0.0	0.04
<b>CETES</b>	0.09	-0.02	0.19	-0.01	-0.1	0.07
<b>IPUS</b>	0.22 **	0.06	0.38	0.28 ***	0.2	0.38
<b>MUI</b>	-0.57 ***	-0.79	-0.35	-0.32 ***	-0.5	-0.17
<b>EPU Global</b>	-0.01 ***	-0.01	0.00	-0.01 ***	-0.01	0.00

	50 <sup>th</sup> Quantile			90 <sup>th</sup> Quantile		
	Coef.	Lower	Upper	Coef.	Lower	Upper
<b>Intercept</b>	7.52	-1.57	16.62	-1.19	-16.12	13.73
<b>IGAE</b>	0.28 **	0.10	0.46	0.48 ***	0.24	0.71
<b>Inflation</b>	0.22 ***	0.12	0.32	0.18 **	0.04	0.31
<b>NER</b>	0.02	-0.01	0.05	-0.03	-0.08	0.02
<b>CETES</b>	-0.14 ***	-0.23	-0.06	-0.09	-0.22	0.03
<b>IPUS</b>	0.27 ***	0.15	0.39	-0.02	-0.23	0.19
<b>MUI</b>	-0.09	-0.22	0.05	0.07	-0.15	0.28
<b>EPU Global</b>	-0.01 ***	-0.01	0.00	0.00	-0.01	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.

Table 10: Estimated Coefficients of Benchmark Model with RER (h = 3 months)  
Apr-94 - Dec-21

	10 <sup>th</sup> Quantile			25 <sup>th</sup> Quantile		
	Coef.	Lower	Upper	Coef.	Lower	Upper
<b>Intercept</b>	43.73 ***	30.73	56.73	31.01 ***	21.7	40.30
<b>IGAE</b>	0.28 **	0.07	0.48	0.41 ***	0.3	0.55
<b>Inflation</b>	0.14 **	0.03	0.25	0.18 ***	0.1	0.26
<b>NER</b>	-0.01	-0.04	0.01	0.00	0.0	0.01
<b>CETES</b>	0.13 **	0.04	0.22	0.03	0.0	0.11
<b>IPUS</b>	0.08	-0.04	0.21	0.10 **	0.0	0.18
<b>MUI</b>	-0.62 ***	-0.80	-0.44	-0.44 ***	-0.6	-0.31
<b>RER</b>	-0.03 *	-0.06	0.00	-0.02	-0.04	0.00

	50 <sup>th</sup> Quantile			90 <sup>th</sup> Quantile		
	Coef.	Lower	Upper	Coef.	Lower	Upper
<b>Intercept</b>	12.49 *	1.50	23.49	-4.13	-15.95	7.70
<b>IGAE</b>	0.52 ***	0.36	0.68	0.50 ***	0.30	0.70
<b>Inflation</b>	0.20 ***	0.14	0.27	0.14 **	0.04	0.25
<b>NER</b>	-0.01	-0.04	0.01	-0.02	-0.07	0.04
<b>CETES</b>	-0.07	-0.15	0.02	-0.09	-0.20	0.02
<b>IPUS</b>	0.08	-0.03	0.19	0.09	-0.12	0.30
<b>MUI</b>	-0.17 *	-0.32	-0.02	0.07	-0.07	0.21
<b>RER</b>	0.00	-0.03	0.02	0.02	-0.04	0.08

Source: Own elaboration.

Notes “\*\*\*”, “\*\*”, “\*” if  $p < 0.01$ ,  $p < 0.05$ , and  $p < 0.1$ , respectively. Lower and Upper indicate the 90% confidence interval.

Table 11: Estimated Coefficients of Benchmark Model with Risk Premium (h = 3 months)  
Apr-94 - Dec-21

	10 <sup>th</sup> Quantile			25 <sup>th</sup> Quantile		
	Coef.	Lower	Upper	Coef.	Lower	Upper
<b>Intercept</b>	40.60 ***	27.82	53.38	30.17 ***	20.8	39.57
<b>IGAE</b>	0.32 ***	0.13	0.50	0.42 ***	0.3	0.56
<b>Inflation</b>	0.16 **	0.05	0.27	0.17 ***	0.1	0.26
<b>NER</b>	-0.03 *	-0.05	0.00	-0.01	0.0	0.01
<b>CETES</b>	0.22 *	0.01	0.42	0.04	-0.1	0.15
<b>IPUS</b>	0.07	-0.04	0.19	0.07	0.0	0.16
<b>MUI</b>	-0.61 ***	-0.80	-0.42	-0.44 ***	-0.6	-0.30
<b>Risk Premium</b>	-0.10	-0.35	0.14	0.00	-0.14	0.13

	50 <sup>th</sup> Quantile			90 <sup>th</sup> Quantile		
	Coef.	Lower	Upper	Coef.	Lower	Upper
<b>Intercept</b>	12.23 **	2.27	22.19	-0.41	-9.64	8.82
<b>IGAE</b>	0.51 ***	0.35	0.68	0.52 ***	0.31	0.72
<b>Inflation</b>	0.21 ***	0.14	0.28	0.14 **	0.05	0.24
<b>NER</b>	-0.01	-0.04	0.01	-0.01	-0.07	0.04
<b>CETES</b>	-0.06	-0.17	0.04	-0.02	-0.24	0.21
<b>IPUS</b>	0.09	-0.03	0.20	0.00	-0.20	0.20
<b>MUI</b>	-0.17 *	-0.32	-0.02	0.04	-0.10	0.18
<b>Risk Premium</b>	-0.01	-0.15	0.12	-0.05	-0.29	0.19

Source: Own elaboration.

Notes “\*\*\*”, “\*\*”, “\*” if  $p < 0.01$ ,  $p < 0.05$ , and  $p < 0.1$ , respectively. Lower and Upper indicate the 90% confidence interval.

## 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:

$$z_{t+h}^{\tau} = \beta_0^{\tau} + \beta_1^{\tau} z_t + \beta_2^{\tau} INF_t + \beta_3^{\tau} NER_t + \beta_4^{\tau} CETES_t + \beta_5^{\tau} IPUS_t + \beta_6^{\tau} MUI_t + \varepsilon_t^{\tau} \quad (13)$$

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)  
Apr-94 - Dec-21

	10 <sup>th</sup> Quantile			25 <sup>th</sup> Quantile		
	Coef.	Lower	Upper	Coef.	Lower	Upper
<b>Intercept</b>	43.99 ***	27.17	60.81	24.28 ***	13.9	34.71
<b>CONS</b>	0.49 ***	0.32	0.65	0.49 ***	0.3	0.64
<b>Inflation</b>	0.08 *	0.00	0.15	0.12 ***	0.1	0.17
<b>NER</b>	-0.03	-0.06	0.01	-0.03 *	-0.1	0.00
<b>CETES</b>	0.23 ***	0.12	0.34	0.08	0.0	0.17
<b>IPUS</b>	0.04	-0.10	0.18	0.05	-0.1	0.16
<b>MUI</b>	-0.67 ***	-0.92	-0.42	-0.36 ***	-0.52	-0.20

	50 <sup>th</sup> Quantile			90 <sup>th</sup> Quantile		
	Coef.	Lower	Upper	Coef.	Lower	Upper
<b>Intercept</b>	13.47 ***	6.54	20.39	-6.15	-15.79	3.50
<b>CONS</b>	0.52 ***	0.41	0.63	0.63 ***	0.46	0.80
<b>Inflation</b>	0.19 ***	0.12	0.26	0.13 ***	0.05	0.22
<b>NER</b>	-0.02 *	-0.05	0.00	0.01	-0.02	0.03
<b>CETES</b>	-0.03	-0.10	0.03	-0.13 **	-0.23	-0.04
<b>IPUS</b>	-0.02	-0.10	0.06	0.04	-0.09	0.18
<b>MUI</b>	-0.18 ***	-0.29	-0.08	0.13	-0.01	0.28

Source: Own elaboration.

Notes “\*\*\*”, “\*\*”, “\*” if  $p < 0.01$ ,  $p < 0.05$ , and  $p < 0.1$ , respectively. Lower and Upper indicate the 90% confidence interval.

Table 13: Estimated Coefficients of Model with Investment (h = 3 months)  
Apr-94 - Dec-21

	10 <sup>th</sup> Quantile			25 <sup>th</sup> Quantile		
	Coef.	Lower	Upper	Coef.	Lower	Upper
<b>Intercept</b>	109.21 ***	58.51	159.90	61.93 ***	33.1	90.77
<b>INV</b>	0.60 ***	0.49	0.70	0.63 ***	0.5	0.75
<b>Inflation</b>	0.68 ***	0.38	0.98	0.54 ***	0.3	0.80
<b>NER</b>	-0.11 **	-0.18	-0.03	-0.06 *	-0.1	-0.01
<b>CETES</b>	0.37 *	0.02	0.71	0.00	-0.3	0.26
<b>IPUS</b>	-0.55 ***	-0.89	-0.20	-0.11	-0.3	0.10
<b>MUI</b>	-1.71 ***	-2.48	-0.95	-0.95 ***	-1.38	-0.52

	50 <sup>th</sup> Quantile			90 <sup>th</sup> Quantile		
	Coef.	Lower	Upper	Coef.	Lower	Upper
<b>Intercept</b>	25.93	-4.60	56.46	1.88	-19.29	23.06
<b>INV</b>	0.67 ***	0.53	0.80	0.67 ***	0.55	0.80
<b>Inflation</b>	0.50 ***	0.22	0.77	0.78 ***	0.54	1.03
<b>NER</b>	-0.10 **	-0.17	-0.03	-0.03	-0.12	0.07
<b>CETES</b>	-0.13	-0.37	0.10	-0.39 ***	-0.64	-0.15
<b>IPUS</b>	-0.03	-0.30	0.24	-0.13	-0.51	0.25
<b>MUI</b>	-0.38	-0.83	0.08	0.05	-0.27	0.37

Source: Own elaboration.

Notes “\*\*\*”, “\*\*”, “\*” if  $p < 0.01$ ,  $p < 0.05$ , and  $p < 0.1$ , respectively. Lower and Upper indicate the 90% confidence interval.

Table 14: Estimated Coefficients of Model with Industrial Production (h = 3 months)  
Apr-94 - Dec-21

	10 <sup>th</sup> Quantile			25 <sup>th</sup> Quantile		
	Coef.	Lower	Upper	Coef.	Lower	Upper
<b>Intercept</b>	42.95 ***	30.60	55.30	37.16 ***	22.5	51.79
<b>IMAI</b>	0.30 ***	0.14	0.47	0.37 ***	0.2	0.56
<b>Inflation</b>	0.16	-0.01	0.32	0.32 ***	0.2	0.46
<b>NER</b>	-0.03	-0.06	0.00	-0.03 *	-0.1	0.00
<b>CETES</b>	0.10	-0.04	0.23	0.01	-0.1	0.14
<b>IPUS</b>	0.09	-0.05	0.24	0.05	-0.1	0.17
<b>MUI</b>	-0.66 ***	-0.85	-0.47	-0.57 ***	-0.79	-0.35

	50 <sup>th</sup> Quantile			90 <sup>th</sup> Quantile		
	Coef.	Lower	Upper	Coef.	Lower	Upper
<b>Intercept</b>	12.56	-2.05	27.18	-6.28	-17.37	4.81
<b>IMAI</b>	0.46 ***	0.30	0.63	0.54 ***	0.34	0.73
<b>Inflation</b>	0.37 ***	0.25	0.48	0.28 ***	0.14	0.42
<b>NER</b>	-0.01	-0.05	0.02	-0.02	-0.07	0.02
<b>CETES</b>	-0.15 **	-0.27	-0.02	-0.14	-0.27	0.00
<b>IPUS</b>	0.13	-0.02	0.29	-0.12	-0.41	0.18
<b>MUI</b>	-0.19	-0.41	0.03	0.13	-0.03	0.30

Source: Own elaboration.

Notes “\*\*\*”, “\*\*”, “\*” if  $p < 0.01$ ,  $p < 0.05$ , and  $p < 0.1$ , respectively. Lower and Upper indicate the 90% confidence interval.

Table 15: Estimated Coefficients of Model with Services (h = 3 months)  
Apr-94 - Dec-21

	10 <sup>th</sup> Quantile			25 <sup>th</sup> Quantile		
	Coef.	Lower	Upper	Coef.	Lower	Upper
<b>Intercept</b>	42.68 ***	28.49	56.87	26.33 ***	18.2	34.43
<b>Services</b>	0.30 **	0.05	0.54	0.46 ***	0.3	0.61
<b>Inflation</b>	0.12 ***	0.06	0.17	0.12 ***	0.1	0.15
<b>NER</b>	-0.03 **	-0.05	-0.01	-0.02 *	0.0	0.00
<b>CETES</b>	0.17 ***	0.09	0.26	0.07 *	0.0	0.14
<b>IPUS</b>	0.03	-0.07	0.13	0.13 **	0.0	0.22
<b>MUI</b>	-0.64 ***	-0.84	-0.43	-0.39 ***	-0.51	-0.26

	50 <sup>th</sup> Quantile			90 <sup>th</sup> Quantile		
	Coef.	Lower	Upper	Coef.	Lower	Upper
<b>Intercept</b>	10.36 *	1.39	19.34	2.07	-7.17	11.31
<b>Services</b>	0.49 ***	0.37	0.61	0.43 ***	0.27	0.60
<b>Inflation</b>	0.14 ***	0.10	0.19	0.16 ***	0.09	0.22
<b>NER</b>	-0.02 *	-0.04	0.00	-0.03	-0.06	0.01
<b>CETES</b>	-0.04	-0.11	0.02	-0.11 **	-0.19	-0.04
<b>IPUS</b>	0.09 *	0.00	0.17	0.04	-0.11	0.20
<b>MUI</b>	-0.13	-0.27	0.00	0.02	-0.12	0.16

Source: Own elaboration.

Notes “\*\*\*”, “\*\*”, “\*” if  $p < 0.01$ ,  $p < 0.05$ , and  $p < 0.1$ , respectively. Lower and Upper indicate the 90% confidence interval.



Table 16: Estimated Coefficients of Model with Employment Level (h = 3 months)  
Jul-98 - Dec-21

	10 <sup>th</sup> Quantile			25 <sup>th</sup> Quantile		
	Coef.	Lower	Upper	Coef.	Lower	Upper
<b>Intercept</b>	12.38 ***	4.71	20.06	12.21 ***	6.2	18.18
<b>IMSS</b>	0.84 ***	0.71	0.96	0.71 ***	0.6	0.78
<b>Inflation</b>	0.19 ***	0.09	0.28	0.13 ***	0.1	0.19
<b>NER</b>	0.02 **	0.01	0.04	0.02 **	0.0	0.03
<b>CETES</b>	-0.09 *	-0.16	-0.01	-0.04	-0.1	0.02
<b>IPUS</b>	0.11 ***	0.04	0.17	0.14 ***	0.1	0.19
<b>MUI</b>	-0.19 ***	-0.30	-0.08	-0.18 ***	-0.27	-0.09

	50 <sup>th</sup> Quantile			90 <sup>th</sup> Quantile		
	Coef.	Lower	Upper	Coef.	Lower	Upper
<b>Intercept</b>	5.12 **	1.17	9.07	3.29	-1.11	7.69
<b>IMSS</b>	0.72 ***	0.65	0.79	0.57 ***	0.41	0.74
<b>Inflation</b>	0.10 ***	0.05	0.14	0.05	-0.02	0.12
<b>NER</b>	0.02 ***	0.01	0.03	-0.02 **	-0.04	-0.01
<b>CETES</b>	-0.05 **	-0.09	-0.02	-0.01	-0.06	0.03
<b>IPUS</b>	0.12 ***	0.09	0.16	0.06 ***	0.03	0.10
<b>MUI</b>	-0.07 *	-0.12	-0.01	-0.02	-0.08	0.05

Source: Own elaboration.

Notes “\*\*\*”, “\*\*”, “\*” if  $p < 0.01$ ,  $p < 0.05$ , and  $p < 0.1$ , respectively. Lower and Upper indicate the 90% confidence interval.

Table 17: Estimated Coefficients of Model with Employment Rate (h = 3 months)  
Apr-94 - Dec-21

	10 <sup>th</sup> Quantile			25 <sup>th</sup> Quantile		
	Coef.	Lower	Upper	Coef.	Lower	Upper
<b>Intercept</b>	4.31 ***	2.69	5.93	4.59 ***	2.6	6.58
<b>EMP</b>	0.59 ***	0.50	0.69	0.61 ***	0.5	0.71
<b>Inflation</b>	0.04 ***	0.02	0.06	0.05 ***	0.0	0.07
<b>NER</b>	-0.01 ***	-0.02	-0.01	-0.01 ***	0.0	-0.01
<b>CETES</b>	0.00	-0.02	0.03	0.00	0.0	0.02
<b>IPUS</b>	0.00	-0.02	0.02	0.00	0.0	0.02
<b>MUI</b>	-0.07 ***	-0.09	-0.05	-0.07 ***	-0.10	-0.04

	50 <sup>th</sup> Quantile			90 <sup>th</sup> Quantile		
	Coef.	Lower	Upper	Coef.	Lower	Upper
<b>Intercept</b>	2.56 ***	1.14	3.98	1.32 **	0.29	2.36
<b>EMP</b>	0.62 ***	0.52	0.71	0.70 ***	0.60	0.81
<b>Inflation</b>	0.06 ***	0.05	0.08	0.05 ***	0.03	0.07
<b>NER</b>	-0.01 **	-0.01	0.00	0.00	-0.01	0.00
<b>CETES</b>	-0.03 ***	-0.05	-0.01	-0.01	-0.03	0.00
<b>IPUS</b>	0.00	-0.03	0.02	0.00	-0.02	0.02
<b>MUI</b>	-0.04 ***	-0.06	-0.02	-0.01	-0.03	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.

## 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 quarterly 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:

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

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.

Table 18: Estimated Coefficients of Model with GDP (yoy) growth (h = 1 quarter)  
94-Q2 - 21-Q4

	10 <sup>th</sup> Quantile			25 <sup>th</sup> Quantile		
	Coef.	Lower	Upper	Coef.	Lower	Upper
<b>Intercept</b>	-1.73 ***	-2.74	-0.73	-0.70 **	-1.2	-0.23
<b>IGAE</b>	0.64 ***	0.37	0.92	0.70 ***	0.5	0.86
<b>Inflation</b>	0.01	-0.08	0.11	0.04	0.0	0.12
<b>FCI</b>	-0.02 **	-0.03	0.00	-0.01 **	-0.01	0.00
	50 <sup>th</sup> Quantile			90 <sup>th</sup> Quantile		
	Coef.	Lower	Upper	Coef.	Lower	Upper
<b>Intercept</b>	-0.02	-0.40	0.35	2.36 ***	1.81	2.92
<b>IGAE</b>	0.62 ***	0.51	0.72	0.49 ***	0.40	0.57
<b>Inflation</b>	0.11 ***	0.06	0.16	0.10 ***	0.07	0.13
<b>FCI</b>	-0.01 ***	-0.01	0.00	0.00	-0.01	0.01

Source: Own elaboration.

Notes “\*\*\*”, “\*\*”, “\*” if  $p < 0.01$ ,  $p < 0.05$ , and  $p < 0.1$ , respectively. Lower and Upper indicate the 90% confidence interval.

## 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:

$$y_{t+h}^{\tau} = \alpha_{\tau} + \beta_{\tau}y_t + \delta_{\tau}\pi_t + \gamma_{\tau}FCI_t + \varepsilon_t^{\tau} \quad (15)$$

Where  $y_t$  is the IGAE annual growth rate,  $\pi_t$  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  $\tau$  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)  
Apr-94 - Dec-21

	10 <sup>th</sup> Quantile			25 <sup>th</sup> Quantile		
	Coef.	Lower	Upper	Coef.	Lower	Upper
<b>Intercept</b>	-1.73 ***	-2.74	-0.73	-0.70 **	-1.2	-0.23
<b>IGAE</b>	0.64 ***	0.37	0.92	0.70 ***	0.5	0.86
<b>Inflation</b>	0.01	-0.08	0.11	0.04	0.0	0.12
<b>FCI</b>	-0.02 **	-0.03	0.00	-0.01 **	-0.01	0.00
	50 <sup>th</sup> Quantile			90 <sup>th</sup> Quantile		
	Coef.	Lower	Upper	Coef.	Lower	Upper
<b>Intercept</b>	-0.02	-0.40	0.35	2.36 ***	1.81	2.92
<b>IGAE</b>	0.62 ***	0.51	0.72	0.49 ***	0.40	0.57
<b>Inflation</b>	0.11 ***	0.06	0.16	0.10 ***	0.07	0.13
<b>FCI</b>	-0.01 ***	-0.01	0.00	0.00	-0.01	0.01

Source: Own elaboration.

Notes “\*\*\*”, “\*\*”, “\*” if  $p < 0.01$ ,  $p < 0.05$ , and  $p < 0.1$ , respectively. Lower and Upper indicate the 90% confidence interval.