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N° 2021-11

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Marco Hernández Vega

Banco de México

July 2021

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The Nonlinear Effect of Uncertainty in Portfolio Flows to Mexico

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Abstract: Economic uncertainty is considered not only one of the main causes of recessions, but also a major obstacle to economic recovery. Recent studies find that significantly high levels of uncertainty could have a non-linear impact that amplifies the response of macroeconomic variables. The objective of this document is to analyze the presence of this impact on portfolio flows to Mexico. The results show that episodes of high uncertainty have a greater negative impact on bond and stock flows than those found under a linear VAR. Furthermore, it is observed that the effect is more persistent for bond flows. Finally, high uncertainty leads to a marked depreciation of the nominal exchange rate, a contraction in economic activity and a fall in the stock index.

Keywords: Foreign Portfolio Investment, Mexican Equity and Bond Market, Uncertainty

JEL Classification: F32, F62, G10

Resumen: La incertidumbre económica se considera no solo una de las principales causas de recesiones, sino también un importante obstáculo para la recuperación económica. Estudios recientes encuentran que niveles significativamente altos de incertidumbre podrían tener un impacto no lineal que amplifica la respuesta de las variables macroeconómicas. El objetivo de este documento es analizar la presencia de dicho impacto sobre los flujos de cartera hacia México. Los resultados muestran que episodios de elevada incertidumbre tienen un impacto negativo de mayor magnitud en los flujos en bonos y acciones que los que se encuentran bajo un VAR lineal. Además, se observa que el efecto es más persistente en los flujos en bonos. Finalmente, una elevada incertidumbre conlleva una marcada depreciación del tipo de cambio nominal, una contracción de la actividad económica y una caída en el índice accionario.

Palabras Clave: Inversión de Cartera Extranjera, Mercado Mexicano de Renta Variable y de Bonos, Incertidumbre

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1 Introduction

Economic uncertainty is considered not only as one of the main causes of recessions, but also as one important obstacle for economic recovery (Basu and Bundick (2017) and Altig et al. (2020)). Research has shown that when uncertainty reaches high levels, it can have negative and significant effects on economic aggregates (like a generalized decline in output, consumption, investment, and employment) and generate a significant increase in stock market volatility (see for example Bloom (2009, 2014) and Basu and Bundick (2017) among others). At the same time, uncertainty can affect the global economy due to the increasing integration in international financial markets, a phenomenon that has gained relevance among policymakers particularly of emerging market economies (EMEs) where elevated uncertainty can lead to significant fluctuations in exchange rates, stock prices, and capital flows reversals with potential damaging risks to financial stability.

Of course, capital flows reversals are not exclusive of EMEs when uncertainty rises but given that investors consider these economies relatively riskier than advanced economies foreign capital tends to move out of EMEs on a larger scale leading, in some cases, to sudden stops (see Forbes and Warnock (2012), Fratzscher (2012) and Gourio et al. (2015)). As a result, studying the effects of uncertainty on capital flows to EMEs have become a popular topic of economic research. For example, Lo Duca (2012) finds that when uncertainty is high, risk aversion behavior has a dominant-negative impact on portfolio flows, but these effects vary a cross-time. Gauvin et al. (2013) show that an increase in policy uncertainty within the US does have a negative significant impact on bond flows to EMEs but that for equities this effect is slightly positive. The authors posit as a possible explanation that higher uncertainty in the US pushes equity investors to find higher returns in EMEs.

Dahlhaus and Vasishtha (2014) show that uncertainty shocks lead to a significant retrenchment of portfolio flows from EMEs but this effect is different across countries and depends on individual macroeconomic fundamentals. Rey (2015) finds that increases in uncertainty tend to have important effects on global asset prices and financial flows and that these effects are substantial in the case of EMEs. Miranda-Agrippino and Rey (2015) provide evidence that US monetary policy is an important driver of global uncertainty and argue that, in an uncertain environment, some EMEs are not able to have both, perfect capital mobility and an independent monetary policy, even under a flexible exchange rate regime. Gelos (2019) documents that significant reversals of capital flows to EMEs took place during periods where uncertainty reached elevated levels, in particular during the global financial crisis (GFC), the European crisis in 2012, and the depreciation of the yuan in 2015. They argue that such reversals posed an important challenge for policymakers in these economies. Bhattarai et al. (2020) find evidence that uncertainty in the US has significant and

persistent negative effects on EMEs exchange rates, stock prices, and capital flows. Furthermore, the authors show that when US uncertainty is very high these effects are transmitted to the real economy.

As described by the works cited above, uncertainty can have important negative effects on capital flows which, in a worst-case scenario, could plunge EMEs into a financial crisis. This phenomenon is even more relevant in the actual juncture where uncertainty caused by COVID-19 reigns over the global economy and has created turbulence in international financial markets. For instance, the pandemic has caused a massive reversal of portfolio flows, which for some EMEs have amounted to close to 1 percent of their GDP, see Beirne et al. (2020).

One aspect that most of the works cited above highlight, is that the response of capital flows to uncertainty shocks is heterogeneous among EMEs and that this occurs due to differences in the strength of their macroeconomic fundamentals and level of integration with international financial markets (see Forbes and Warnock (2012), Fratzscher (2012), Lo Duca (2012), Dahlhaus and Vasishta (2014), among others). Given such heterogeneity, it is also important to study the impact of uncertainty on individual countries.

In this context, some recent works analyze the effects of uncertainty in Mexico. For example, Bush and Noria (2019) show that uncertainty generated abroad tends to rise foreign exchange rate volatility even more than uncertainty produced by domestic factors. In turn, Ibarra and Tellez-Leon (2019) analyze the response of FDI, portfolio flows, and other investment to global uncertainty (among other push and pull factors). They find that global uncertainty is associated with a reduction in portfolio and other investment flows. Lastly, Cebreros et al. (2020) show that trade policy uncertainty has significant negative effects on FDI being such effects stronger in states where exporting plays a major role.

Nevertheless, one characteristic not undertaken in the works cited above is the possibility that when uncertainty attains a very high level, it could also have a nonlinear effect that amplifies the response of macroeconomic variables. Recent literature (Caggiano et al. (2017), Mumtaz and Theodoridis (2017), Carriero et al. (2018), Shin and Zhong (2018), and Jackson et al. (2019)) that analyzes the impact of uncertainty shocks in the real economy show that when uncertainty is high, a nonlinear channel emerges directly affecting how shocks propagate across macroeconomic variables.

This work contributes to the literature by taking into account the previous aspects. On one hand, we center our attention on the particular case of portfolio flows to Mexico, which is not only among the most integrated EMEs in international financial markets but also has a very close economic relationship with the US economy which has been the country where several uncertainty

shocks have originated (like the global financial crisis, the taper tantrum, the government shutdown in 2014, and the imposition of tariffs).

On the other hand, we study the presence of a nonlinear effect of uncertainty shocks. We do so by adopting Jackson et al. (2019) max uncertainty VAR model. One of the advantages of this model is that the nonlinear channel is activated only in episodes of elevated uncertainty, whereas in normal times only the linear effect is present. Also, the model introduces a time-varying threshold so that the magnitude and persistency of the response of capital flows will depend on the size of the uncertainty shock.

Our results agree with those in Ibarra and Tellez-Leon (2019) in the sense that uncertainty does have a negative effect on portfolio flows to Mexico, but that when a nonlinear channel is taken into account, the response of bond and equity flows is significantly bigger than in a linear model. In particular, at the time the shock takes place the response could be up to five times larger. Our findings also point to a longer persistency in the nonlinear model for bond flows where the impact of uncertainty remains significant two months after the shock while in the linear case it is only one month. In turn, the response of equity flows is only significant at the time of the shock in the nonlinear model but not significant in the linear model. These results are robust to the use of a different measure of uncertainty, such as the US economic policy uncertainty index (EPU), and the use of different measures of economic activity such as the Global Indicator of Economic Activity (IGAE).

The paper is organized as follows: in the next section, we describe our measure of uncertainty. The third section shows some stylized facts about portfolio flows dynamics during high uncertainty periods. The fourth section shows the construction and estimation of the max uncertainty VAR. The fifth provides details on the computations of the impulse responses. The sixth presents empirical results. Section seven concludes.

2 Measuring Global Uncertainty

After the global financial crisis (GFC), the world economy has faced several periods of elevated uncertainty increases caused by diverse economic and political events, such as the euro area crisis, the fall in oil prices in the last months of 2014, the Chinese stock market crash and depreciation of the yuan in mid-2015, and more recently the pandemic caused by COVID-19 to mention some.

To analyze the effects on uncertainty it is important, first, to have a good measure at hand. Several institutions and researchers have put big efforts to provide a good measure. For example, the economic policy uncertainty index of Baker et al. (2016) based on newspapers search of key

economic concepts; a time-varying macroeconomic uncertainty index obtained using more formal econometric methods proposed by Jurado et al. (2015); indicators based on survey data, such as the one provided by the Survey of Professional Forecasters; and measures of implied stock market volatility like the Chicago Board Exchange VIX; among others.

In this work, we opt for using the VIX index as a measure of uncertainty. The VIX is available at almost any frequency (daily, weekly, monthly, etc) and is the most common indicator used in the capital flows literature. But how well does this index perform as an uncertainty indicator? The answer to this question is that the VIX does quite well by showing significant increases in episodes where uncertainty and risk aversion dominated the economic and financial landscape.¹

For example, during the period between November 2006 and October 2014 (Figure 1a), the biggest increases in the VIX took place at the beginning of the subprime crisis in July-August 2007, at the dawn of the GFC (September 2008), at the beginning of the euro area crisis (May 2010), and all through the debt ceiling debate in the US (July-Sept 2011). Surprisingly, the increase in the VIX during the taper tantrum and the shutdown of the US government was not as big as in the previously mentioned episodes. Observing the dynamics of the VIX from November 2014 up to July 2020 (Figure 1b) we find that the biggest increases in the index took place at the time of the dramatic fall in oil prices in December 2014, the depreciation of the yuan in August 2015, the Volpocalypse shock in February 2018, the intensification of the China-US trade tensions at the end of 2018, and the COVID-19 pandemic.² All this makes us confident in the appropriateness of the VIX as a measure of uncertainty.

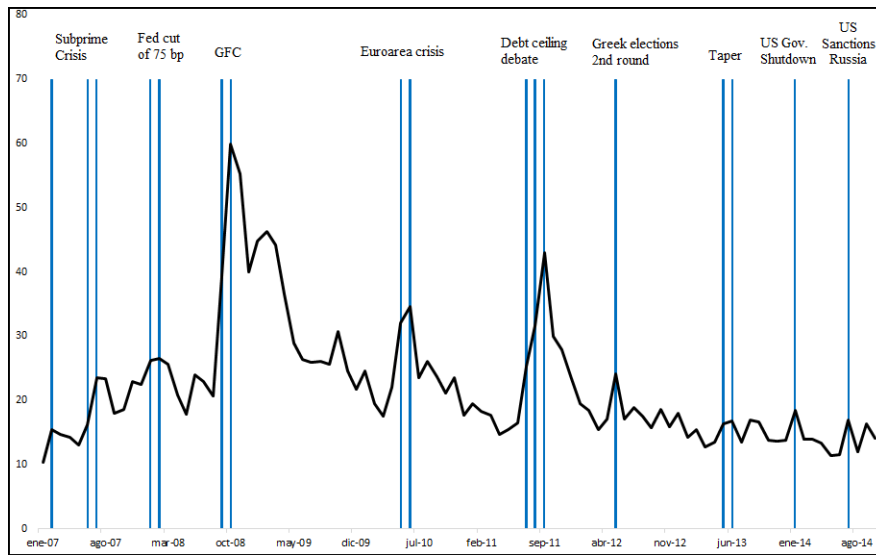
3 Portfolio Flows During High Uncertainty Periods

Taking advantage of the availability of high-frequency data provided by Emerging Portfolio Fund Research (EPFR) we focus on studying the response of portfolio flows in Mexico to uncertainty shocks. According to Jotikasthira et al. (2012) and Fratzscher (2012), EPFR data provide a good approximation despite only covering around 20 percent of the total amount reported in the Balance of Payment statistics. EPFR reports investment of around 24,000 equity funds and 19,000 bond funds domiciled in several advanced economies. Also, one characteristic of EPFR data that must be taken into account is that most of the information reported corresponds to the position of funds located in the US, although EPFR has been broadening its coverage to funds from the euro area and the UK since 2010.

¹Note that the time series of the VIX is divided into two periods in Figures 1a and 1b to clearly show the relationship between this index and the events leading to high uncertainty periods.

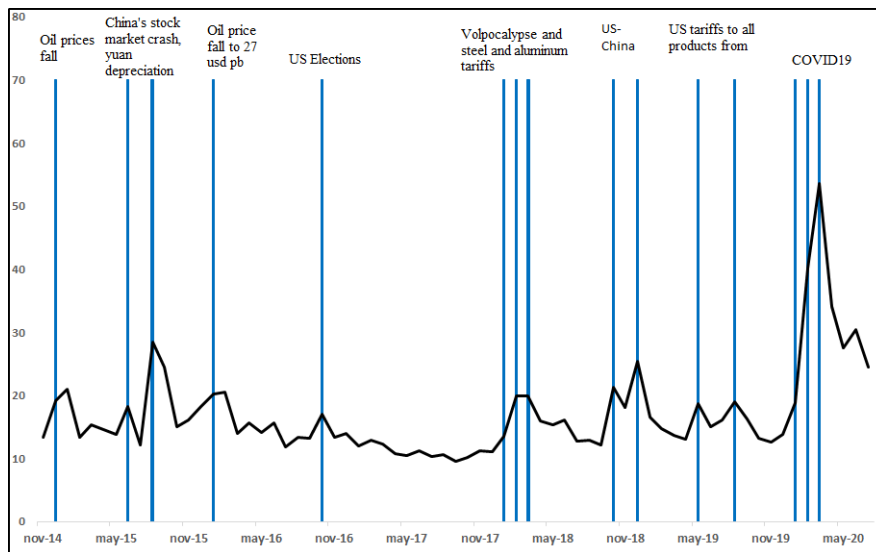
²For more details about all the events described in Figure 1a and 1b see Appendix C.

Figure 1a: VIX Index from January 2007 to October 2014



Source: Bloomberg.

Figure 1b: VIX Index from November 2014 to July 2020

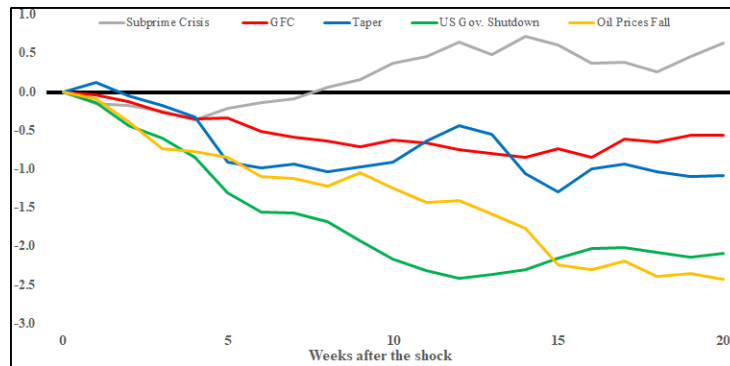


Source: Bloomberg.

As shown by Forbes and Warnock (2012), Fratzscher (2012), Lo Duca (2012), Dahlhaus and Vasishtha (2014), and Beirne et al. (2020), when uncertainty rises portfolio flows tend to fall. However, each episode of elevated uncertainty has had an impact of different magnitude and persistency. For example, for the case of Mexico, looking at the period 2007 – 2014 equity flows fell for 7 weeks during the subprime crisis shock and recovered after the 8th week, while the GFC led

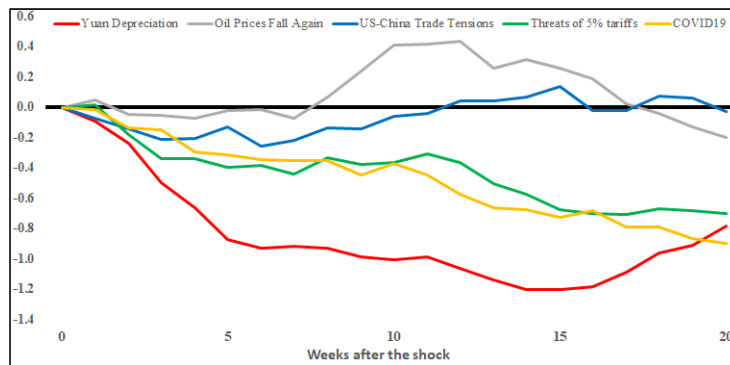
to a constant fall in equity up to 20 weeks after the shock. The same occurred during the taper tantrum episode, during the US government shutdown in January 2014, and when oil prices plunge in December 2014. Furthermore, the US government shutdown and the plunge in oil prices had a bigger impact on equity flows, see Figure 2a.

Figure 2a: Accumulated Equity Flows to Mexico after Selected High Uncertainty Episodes
In Billions of USD



Source: EPFR.

Figure 2b: Accumulated Equity Flows to Mexico after Selected High Uncertainty Episodes
In Billions of USD

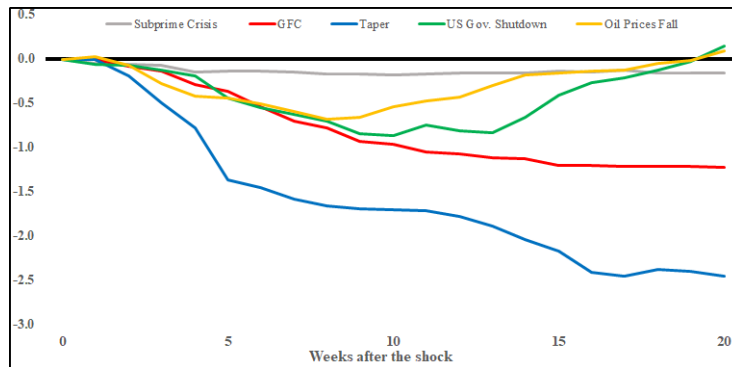


Source: EPFR.

Now, when looking at the uncertainty episodes observed during the period 2015 – 2020 it could look surprising that the period of the yuan depreciation had a bigger negative impact on equity flows to Mexico than, for example, the COVID-19 pandemic. However, keep in mind that the depreciation of the yuan took place in August 2015 and flows were just recovering from the plunge in oil prices at the end of 2014. The few months between these two shocks may have prompted investors to shift bigger amounts of investment to a more secure place at that time, Figure 2b.

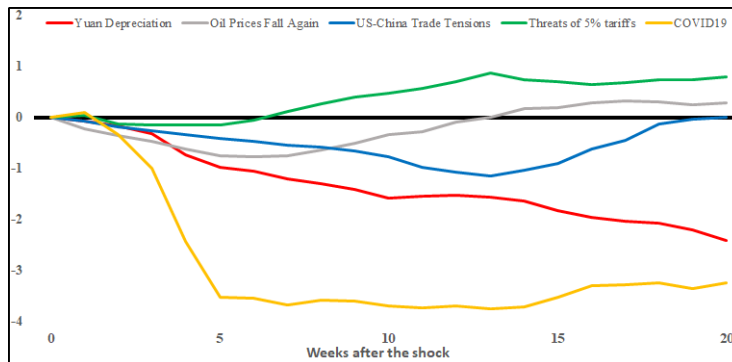
Similarly, bond flows have been affected negatively by periods of elevated uncertainty. For instance, the taper tantrum episode led to an important retrenchment that even surpassed the one observed during the GFC, see Figure 3a. One caveat that must be considered when looking at bond flows data from EPFR is that the number of equity funds (around 16,000) tracked by EPFR was almost twice as big as the number of bonds funds (9,000) in 2008 – 2009. Since then, the bond funds tracked by EPFR have risen significantly. This helps to explain why during the taper tantrum the reversal of bond flows was bigger than during the GFC.

Figure 3a: Accumulated Bond Flows to Mexico after Selected High Uncertainty Episodes
In Billions of USD



Source: EPFR and author calculations.

Figure 3b: Accumulated Bond Flows to Mexico after Selected High Uncertainty Episodes
In Billions of USD



Source: EPFR and author calculations.

Among the most recent periods of high uncertainty, the COVID-19 pandemic has had the most negative effects on bond flows followed by the depreciation of the yuan, see Figure 3b. In contrast to what we saw for equity, an increase in the US-China trade tensions had a more persistent negative

impact on bonds but the threat by the US of imposing a 5 percent tariff on all products from Mexico had only a smaller effect that lasted only for 5 weeks.

4 Data

The literature on capital flows state that these have two main determinants: push and pull factors. Push factors are variables that represent global economic and financial conditions. Pull factors are those variables that represent the recipient economy's domestic conditions which make it attractive or unattractive to foreign investment. Thus, we gather data on the most common push and pull factors found in the literature.

With respect to push factors, we use US industrial production index, s.a. (IP_t^*) and the 3-month Libor-OIS as representing short-run interest rates (i_t^*). As pull factors, we use the peso/dollar nominal exchange rate (FX_t), Mexico's industrial production index, s.a. (IP_t), the 3-month interbank rate (i_t), and Mexico's stock market index (SM_t).

All data is gathered at a monthly frequency from January 2006 to July 2020.³ Both Industrial production indices and the stock market index are transformed into log-differences. The nominal exchange rate is introduced in growth rates. Interest rates, the VIX index, as well as bond and equity flows will enter in levels. The source of the data is Bloomberg, Haver Analytics and EPFR.⁴

5 Methodology

To account for the possible nonlinear effect of uncertainty on portfolio flows, this work estimates the max uncertainty VAR designed by Jackson et al. (2019). This model is characterized by allowing the level of uncertainty to determine how it affects the endogenous variables. As a result, the effects are time-varying. Also, this model is easier to compute with respect to other time-varying thresholds models which depend on two-sided filters to determine the threshold value. The main assumption in this model is that only when uncertainty reaches a level above the maximum value observed in the previous m -periods observed m -periods ahead, it has a nonlinear effect. In other words, let Z_t stand for the uncertainty variable and \hat{Z}_t reflect the percentage increase in the level of uncertainty (max uncertainty series hereafter), then

³EPFR data begins in the second half of 2004, during 2005 there was an increase in the number of reporting funds. With the purpose to control for the increase in reporting funds we selected 2006 as the initial year in our analysis.

⁴All variables are stationary, see Appendix B.

$$\hat{Z}_t = \max \left\{ 0, \frac{Z_t - \max \{Z_{t-1}, \dots, Z_{t-m}\}}{\max \{Z_{t-1}, \dots, Z_{t-m}\}} \right\} \quad (1)$$

The max uncertainty series does a very good job capturing most of the episodes where the VIX index rose significantly. For example, the early subprime crisis events in 2007, the GFC, the European crisis, the debt ceiling debate, the depreciation of the yuan, the COVID-19 pandemic, etc. (see Figures 4a and 4b). We choose $m = 3$ since with this value the Max Uncertainty indicator captures all 31 episodes reported in the paper that led to spikes in uncertainty plus two additional increases in the VIX not directly related to known periods of elevated uncertainty; i.e. $\hat{Z}_t > 0$ occurs 33 times in the sample. Selecting a different value for m implies having a less ideal measure. For example, if $m = 2$, $\hat{Z}_t > 0$ at 37 different dates so that there are now 6 more increases in the VIX not directly linked to known uncertainty episodes. In turn, if $m = 4$, \hat{Z}_t is bigger than zero 29 times leaving out 2 episodes. Hence, using this simple criterion $m = 3$ was selected.

Once we have verify that \hat{Z}_t is an adequate indicator of episodes of elevated uncertainty, we then proceed to formulate and estimate the max uncertainty VAR. Let the US variables (push factors) be grouped in the vector X_t , and the Mexican variables (pull factors) together with the flow variables be included in a vector Y_t . Then, the max uncertainty VAR is given by:

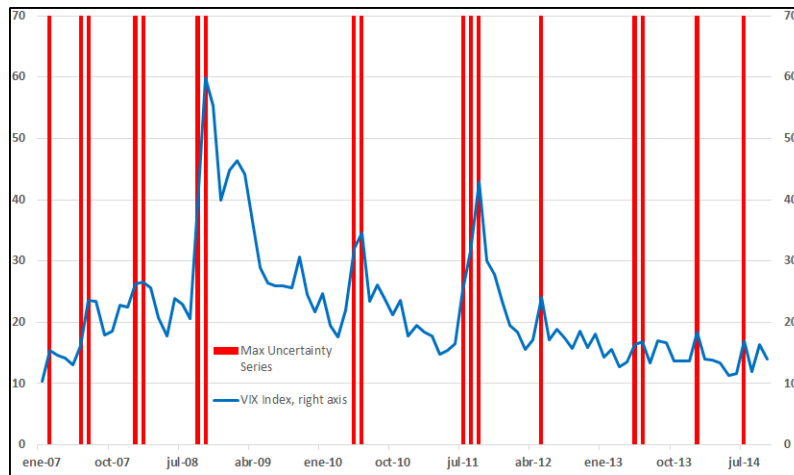
$$\begin{bmatrix} Z_t \\ X_t \\ Y_t \end{bmatrix} = \begin{bmatrix} \beta^{ZZ}(L) & \beta^{ZX}(L) & 0 \\ \beta^{XZ}(L) & \beta^{XX}(L) & 0 \\ \beta^{YZ}(L) & \beta^{YX}(L) & \beta^{YY}(L) \end{bmatrix} \times \begin{bmatrix} Z_{t-1} \\ X_{t-1} \\ Y_{t-1} \end{bmatrix} + \begin{bmatrix} 0 \\ \hat{\beta}^{XZ}(L) \\ \hat{\beta}^{YZ}(L) \end{bmatrix} \times \hat{Z}_{t-1} + \begin{bmatrix} \varepsilon_t^Z \\ \varepsilon_t^X \\ \varepsilon_t^Y \end{bmatrix} \quad (2)$$

where the β coefficients are the parameters to estimate, and ε_t^Z , ε_t^X and ε_t^Y are the reduced-form errors which have a normal distribution with zero mean and variance-covariance matrix Σ .

Note that neither uncertainty (Z_t) nor the US variables (X_t) are affected by lags in Mexico's variables (hence the zero restrictions observed) because it is a small open economy. However, US variables are allowed to have an impact on uncertainty.

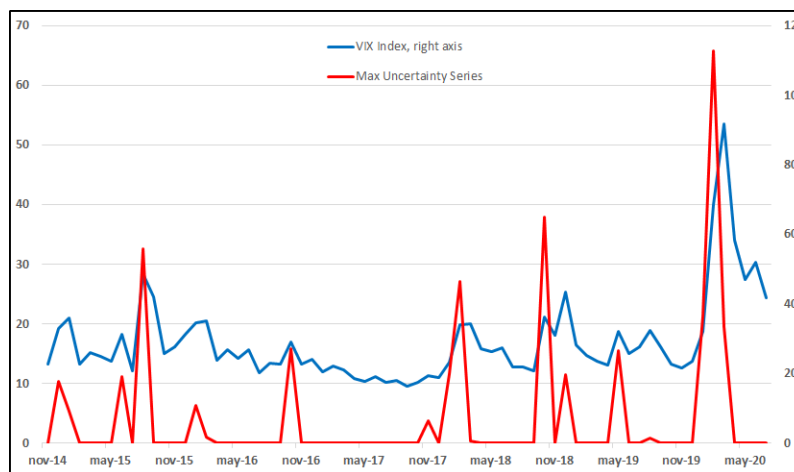
Equation 2 shows that when uncertainty is low ($\hat{Z}_t = 0$), bond and equity flows are only affected linearly through the lag polynomial $\beta^{YZ}(L)Z_{t-1}$. However, when uncertainty is high its impact is amplified by $\beta^{YZ}(L)Z_{t-1} + \hat{\beta}^{YZ}(L)\hat{Z}_{t-1}$.

Figure 4a: VIX Index and Max Uncertainty Series (\hat{Z}), January 2007 to October 2014



Source: Bloomberg and authors calculations.

Figure 4b: VIX Index and Max Uncertainty Series (\hat{Z}), November 2014 to July 2020



Source: Bloomberg and author calculations.

5.1 Estimation and Impulse Response Functions

Two different specifications of Equation 2 are used depending on whether we are analyzing bond flows or equity flows. As mentioned before each version is composed by three blocks: The first contains the uncertainty indicator. The second represents the push factors, which as explained in the capital flows literature are fully exogenous in the case of a small open economy like Mexico. Lastly, the domestic block containing pull factors as well as the respective flows variables.

In the version for bond flows, the transmission mechanism is assumed to be as followed: When global uncertainty rises, it first has an effect push factors (US industrial production and the Libor-

OIS rate) which at the same time affect the Mexican economy. The uncertainty shock is first felt by the nominal exchange rate (FX), which works as shock absorber. As the negative shock also affects economic activity and monetary policy is adjusted to minimize its effects it leads to changes in interest rates (interbank rate). Finally, as interest rates change, it affects bond flows.

The specification for equity flows is somewhat different. The variables it includes are the VIX, the US industrial production, the nominal exchange rate, Mexico's industrial production, the Mexican stock market index and equity flows. The reason why the interest rates are left out is because equity investors are mostly concern with stock prices or dividends they will received by their holdings of stocks which, at the same time, depend mostly on firms' profitability rather than on interest rates.

Equation 2 is estimated through Bayesian methods. Following Jackson et al. (2019), we assume a normal-inverse Wishart prior distribution for the reduced form parameters and also assume that they have zero mean and are uncorrelated. Hence, the posterior distribution will also be a normal-inverse Wishart.⁵ The VAR is estimated using one lag of the dependent variables as suggested by both, the Bayesian information criterion (BIC) and the Hannan-Quinn information criterion, see Appendix D.

It is important to highlight that the magnitude of the uncertainty's impact over all the other endogenous variables will depend on the value of \hat{Z}_t , which will be different at every t.⁶ In this case, Koop et al. (1996) argue that traditional impulse response functions can suffer from composition problems and shock dependence as well as being invariant to the history of the data; in other words, in traditional impulse responses the propagation of the shock is not affected by the recent levels of uncertainty whether this has been low or high. Thus, the authors suggest the use of generalized impulse response functions (GIRFs) which would depend on the history of uncertainty. These are obtained as follows, let Ω_t be a story and consider a shock of size δ then

$$GIRF_k(\delta) = E_t [y_{t+k} | \Omega_{t-1}, \varepsilon_t = \delta] - E_t [y_{t+k} | \Omega_{t-1}, \varepsilon_t = 0] \quad (3)$$

Note that the first term in the right hand side is the expectation of y_{t+k} conditional on history Ω_{t-1} , and on a shock of size δ to the i^{th} variable. The second term is the expectation of y_{t+k} conditional on the observed history. This second term is also known as the baseline profile of y_{t+k} .

⁵Posterior draws are obtained from the Gibbs sampler using 16,000 thousands simulations after discarding the first 4000.

⁶Remember that when $\hat{Z}_t > 0$ its has different levels in most of the cases. For example, \hat{Z}_t was equal to 64.47 percent in September 2008 but its level in February 2020 was 112.90 percent.

The GIRFs have the advantage that they are unique and invariant to the order of the endogenous variables in the VAR. The computation of the GIRFs is carried out by using Monte Carlo methods.⁷ To be able to compare the GIRFs against the traditional impulse responses we set δ to be equal to a one standard deviation of the VIX.

Now, before passing to the results section it is important to analyze if equation 2 is the appropriate one. In other words, it is important to know if the Max Uncertainty indicator plays a significant role. This is achieved by following Schmidt (2019) and performing nonlinearity tests to each equation of the VAR. The null hypothesis state that the term $\hat{\beta}^{YZ}(L)$ should be equal to zero. Nevertheless, the author mentions that the problem with such test is that the thresholds are not identified under the null and one must relied in performing a sub-Wald test. Again, following Schmidt (2019) the sup-Wald statistic (W^*) is defined as:

$$W^* = \sup_{\omega} W(\hat{Z}_{t-1})$$

Finally, to obtain the asymptotic p-values of the sup-Wald test it is necessary to implement the bootstrap method of Hansen (1996). The null is rejected at the 10 percent level of significance in both equations indicating that for the equations for the nominal exchange rate, the stock market, bond flows and portfolio flows the Max Uncertainty indicator is significant, i.e. that periods of elevated uncertainty do have nonlinear effects, see Table 1.

Table 1: Sup-Wald Test for Nonlinearities

Equation	p-values
VAR for Bond Flows	
Nominal Exchange Rate	0.085*
Industrial Production	0.178
Interest Rate	0.116
Bond Flows	0.069*
VAR for Equity Flows	
Nominal Exchange Rate	0.089*
Industrial Production	0.191
Stock Market Index	0.058*
Equity FLOws	0.051*

Only the p-values for Mexico's variables are shown.
 *** significant at 1%, ** significant at 5%, * significant at 10%

⁷Details about how to compute the GIRF are shown in the appendix.

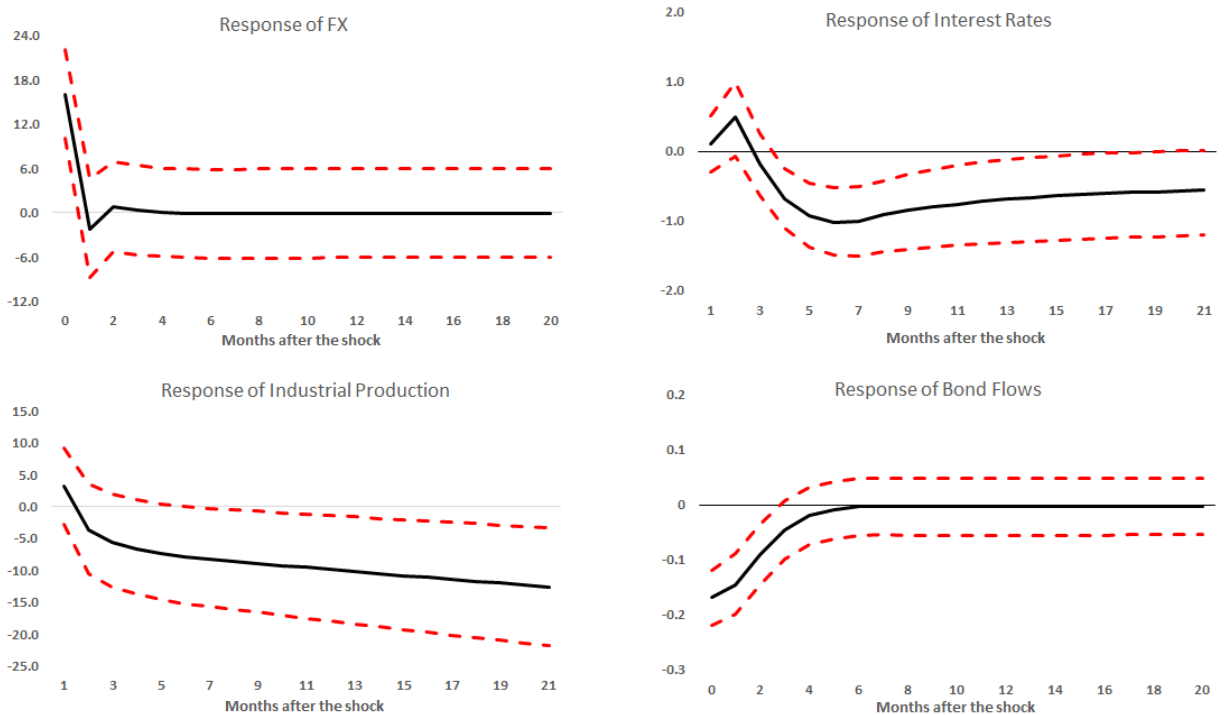
6 Results

This section discusses the results. We begin by analyzing the response of bond flows to an increase in uncertainty. Then, we analyze the case for equity flows. We will report only the responses of Mexico's variables since these are the ones that concern our analysis.

6.1 Uncertainty Effect on Bond Flows

The response of pull factors and bond flows to a positive standard deviation shock in uncertainty is shown in Figure 5. Following the ordering of the VAR, we observe that a positive uncertainty shock leads to a significant depreciation of the nominal exchange rate of 16 percentage points. Mexico's industrial production exhibits a minor increase, but this is not statistically significant different from zero. Similarly, the interest rate shows a small and not significant rise. In turn, higher uncertainty results in a statistically significant retrenchment of bond flows of 0.16 billion dollars.

Figure 5: Generalized Impulse Response Functions



Note. The black solid line is the median response while the red dashed lines stand for the 68 percent credible set. Cumulative impulse responses are reported for the data in log-differences.

This uncertainty shock does not have persistent effects in the nominal exchange rate, which rate of growth returns to its previous level one month after the shock. Nevertheless, uncertainty

has lasting effects in Mexico's industrial production index. The higher uncertain environment reduces the index persistently indicating a continuous contraction of economic activity albeit at a slower pace. As a response to this less dynamic economic activity, the interest rate also decreases three months after the shock and this fall last for four months more. It then gradually returns to its initial level. Finally, the retrenchment in bond flows last for two months after the shock. This will represent an outflow of nearly 0.5 billion dollars in this period.

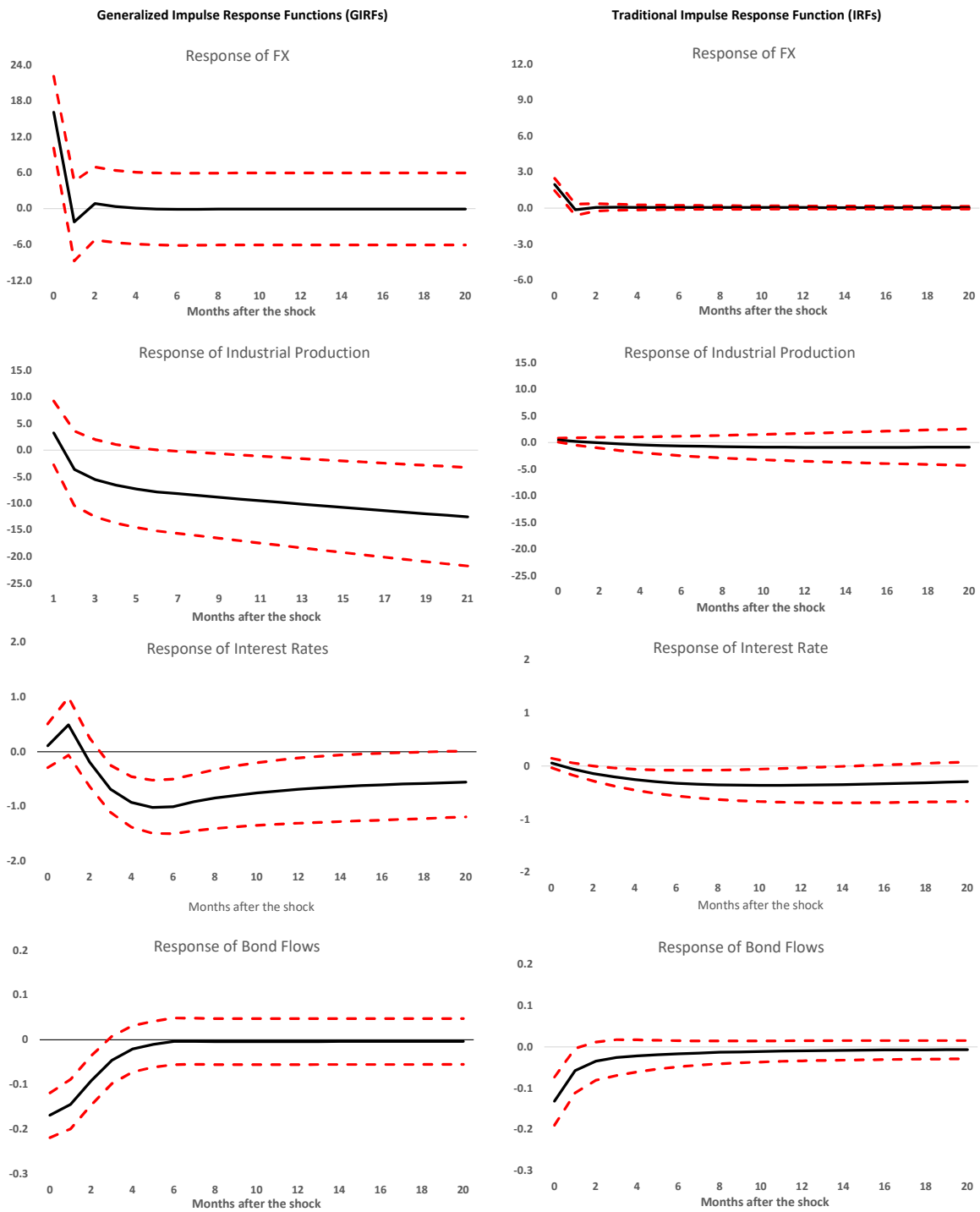
If we compare the response of bond flows in the nonlinear model against the linear one we observe that the fall in bonds at the time of the shock is bigger, 0.16 billions in the first case against 0.12 billions in the second. Another difference is that the response in the nonlinear VAR is significantly different from zero two months after the shock while it is only significant one month after in the linear case, see Figure 6. Furthermore, the depreciation of the exchange rate is significantly bigger in the nonlinear case. The industrial production increases a little more in the linear model, but its fall in the months following the shock is higher in the nonlinear case. Lastly, a similar case can be observed for the interest rate which fall is bigger in magnitude in the nonlinear case.

6.2 Uncertainty Effect on Equity Flows

In this case, as in the previous one, the rise in global uncertainty drives the nominal exchange rate up by 18 percentage points at the time of the shock. Mexico's industrial production index rises slightly, but as before this effect is not statistically significant. In turn, this now more uncertain environment leads to a drastic fall in Mexico's stock market index and a significant decrease in equity flows of 0.8 billion dollars at the time of the shock. Regarding the persistency of the shock, and like the case of bond flows, we observe that this does not have a lasting impact on the nominal exchange rate. However, it does have a negative and very persistent effect on industrial production. After the shock, the stock market index recovers gradually but ends up at a lower level than the one it had before the shock. Finally, equity keeps on falling for one month after the rise in uncertainty which, in cumulative terms, represent a retrenchment of around 1.32 billion dollars, see Figure 7.

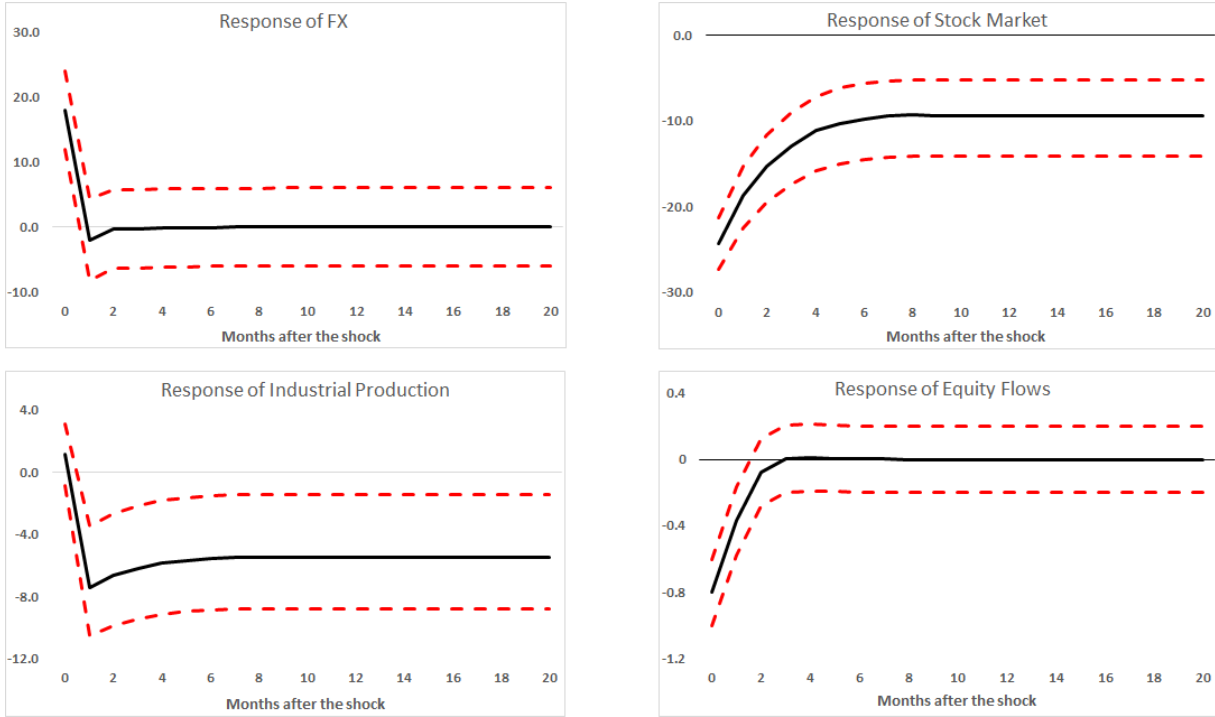
When comparing the GIRFs with the traditional impulse response function we observe, as in the previous case, that there is an important difference in the magnitude between them. In particular, at the time of the shock the fall in equity flows is four times bigger in the nonlinear case. Moreover, in the linear model equity flows actually become positive two months after the shock while in the nonlinear case these flows return to its previous level. In turn, the contraction of industrial production and the stock market indices is drastically higher and more persistent in the nonlinear case, see Figure 8.

Figure 6: Generalized vs Traditional Impulse Response Functions for Bonds



Note. Traditional IRFs are the posterior median responses obtained from equation 2 with $\hat{\beta}^{YZ}(L) = 0$. Cumulative impulse responses are reported for the data in log-differences.

Figure 7: Generalized Impulse Response Functions



Note. The black solid line is the median response while the red dashed lines stand for the 68 percent credible set. Cumulative impulse responses are reported for the data in log-differences.

7 Robustness Tests

The onset of the COVID-19 pandemic resulted in a diverse set of shocks that affected the global economy. In particular, besides the uncertainty shock, during the first half of 2020 a supply and demand as well as a financial shock hit the economy at the same time. This could have exacerbated the response of portfolio flows. To assess if our responses are affected by such problem we estimate our nonlinear model with data up to December 2019 inclusive. Our results came out quite robust and the magnitude and shape of bond and portfolio flows remain practically the same, see Appendix G.

One explanation for why our model does not appear to be affected by the inclusion of the COVID-19 period is because the GIRFs are estimated differently from traditional IRF. Looking at equation 3, it is easier to see that the GIRFs are the expectation of the endogenous variables conditioned on their history (Ω) and the shock (δ) over a baseline case where there is no shock.

In addition, the following robustness tests were performed: First, we change our measure of uncertainty to be the economic policy uncertainty index (EPU) constructed by Baker et al. (2016). Using this measure we calculate \hat{Z}_t^{EPU} an estimate the max uncertainty VAR. The main difference

between the EPU and the VIX resides in their magnitude, EPU has a standard deviation of 32.12 while the VIX has a standard deviation of 8.2. Also, the number of times that $\hat{Z}_t^{EPU} > 0$ (47 times) is higher than $\hat{Z}_t^{VIX} > 0$ (33 times). However, the results are quite robust and no change in the shape or persistency of the impulse responses is observed when using the EPU, see Appendix G.

Second, we use Mexico's General Index of Economic Activity (IGAE in Spanish) instead of the industrial production index. The results do not change, see Appendix H.

8 Conclusion

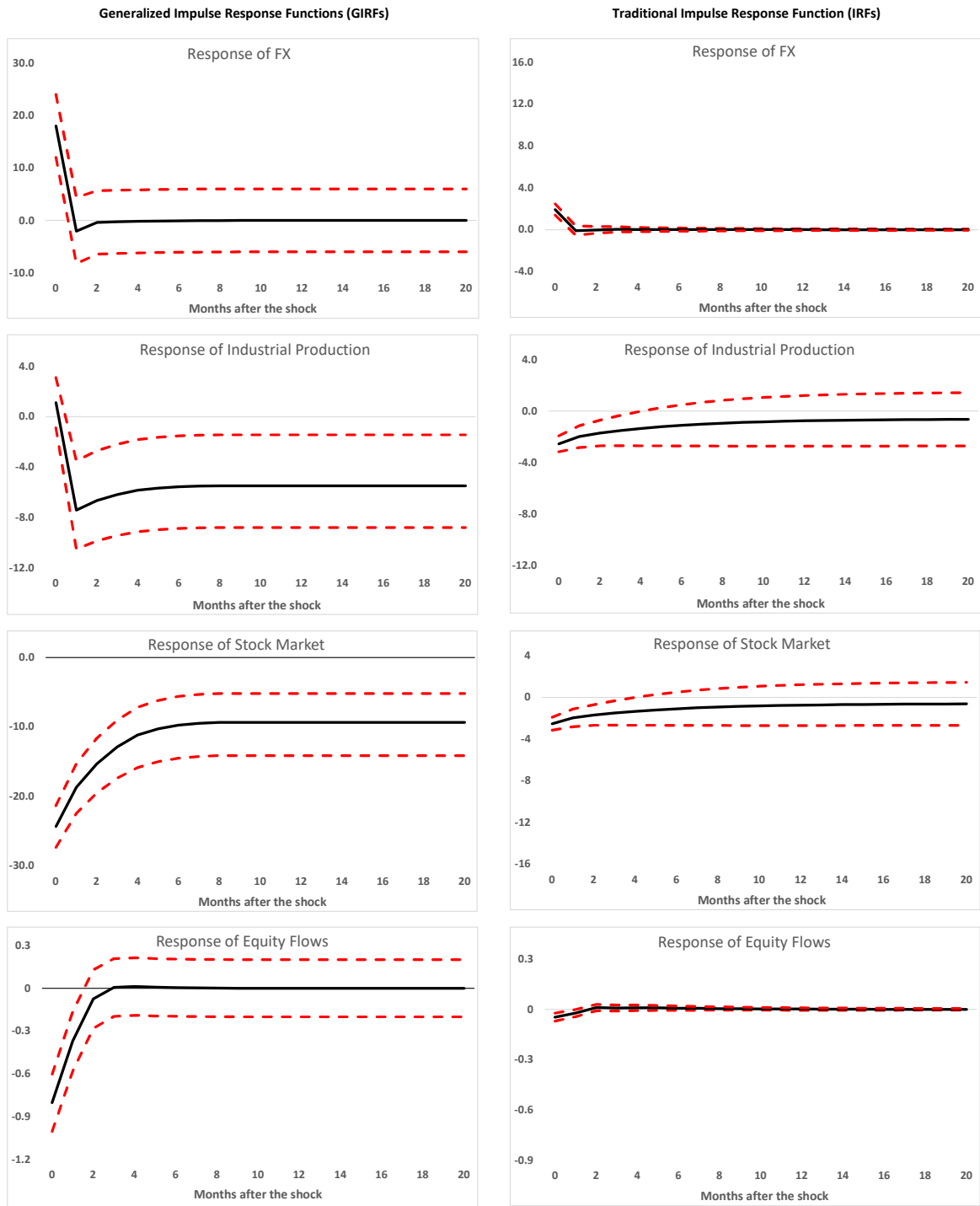
Recent literature has found that when uncertainty reaches high levels it could also have a nonlinear impact that amplifies the response of macroeconomic variables. This work contributes to the literature by studying the presence of a nonlinear effect of uncertainty in portfolio flows to Mexico. We do so by adopting Jackson et al. (2019) max uncertainty VAR model which has the advantage of having a nonlinear effect on the endogenous variables only when uncertainty surpasses a time-varying threshold. Therefore, the magnitude and persistency of the responses will depend on the size of the shock.

The results point to a strong negative impact of uncertainty on both, bond and equity flows. Albeit with some differences in the persistency of the shock. The negative response of bond flows is significant two months after the shock while that of equity flows is significant only at the time of the shock. Also, the fall in equity flows at the time of the shock is higher than that of bond flows. One possible explanation for such differences may be the different way in which equity and bond funds react. According to Lo Duca (2012) and Hernandez-Vega (2017) bond funds tend to have a somewhat slower reaction than equity funds since they may first want to analyze all information available.

In turn, an increase in uncertainty leads to an important depreciation of the peso against the dollar but this effect only lasts for one month. In addition, higher uncertainty leads to a reduction in economic activity and on the stock market index. About the interest rate, the nonlinear impact leads to a marked fall in this variable four months after the shock but then it reverts this trend in the next four months.

When comparing the nonlinear impulse response against the ones obtained by estimating a traditional lineal VAR we observe that uncertainty has stronger negative effects in the nonlinear case. These results are robust to different measures of uncertainty, such as the economic policy uncertainty index, and the use of different measures of economic activity.

Figure 8: Generalized vs Traditional Impulse Response Functions



Note. Traditional IRFs are the posterior median responses obtained from equation 2 with $\hat{\beta}^{YZ}(L) = 0$. Cumulative impulse responses are reported for the data in log-differences.

References

- Altig, D., Baker, S., Barrero, J.M., Bloom, N., Bunn, P., Chen, S., Davis, S.J., Leather, J., Meyer, B., Mihaylov, E., Mizen, P., Parker, N., Renault, T., Smietanka, P., Thwaites, G., 2020. Economic uncertainty before and during the COVID-19 pandemic. *Journal of Public Economics* 191, 104274. doi:10.1016/j.jpubeco.2020.104274.
- Baker, S.R., Bloom, N., Davis, S.J., 2016. Measuring economic policy uncertainty. *The Quarterly Journal of Economics* 131, 1593–1636. doi:10.1093/qje/qjw024.
- Basu, S., Bundick, B., 2017. Uncertainty shocks in a model of effective demand. *Econometrica* 85, 937–958. doi:10.3982/ecta13960.
- Beirne, J.B., Renzhi, N., Sugandi, E.A., Volz, U., 2020. Financial Market and Capital Flow Dynamics During the COVID-19 Pandemic. ADBI Working Papers 1158. Asian Development Bank Institute. URL: <https://ideas.repec.org/p/ris/adbiwp/1158.html>.
- Bhattarai, S., Chatterjee, A., Park, W.Y., 2020. Global spillover effects of US uncertainty. *Journal of Monetary Economics* 114, 71–89. doi:10.1016/j.jmoneco.2019.05.008.
- Bloom, N., 2009. The impact of uncertainty shocks. *Econometrica* 77, 623–685. doi:10.3982/ecta6248.
- Bloom, N., 2014. Fluctuations in uncertainty. *Journal of Economic Perspectives* 28, 153–176. doi:10.1257/jep.28.2.153.
- Bush, G.R., Noria, G.L., 2019. Uncertainty and exchange rate volatility: The case of Mexico. SSRN Electronic Journal doi:10.2139/ssrn.3283374.
- Caggiano, G., Castelnuovo, E., Pellegrino, G., 2017. Estimating the real effects of uncertainty shocks at the zero lower bound. *European Economic Review* 100, 257–272. doi:10.1016/j.euroecorev.2017.08.008.
- Carriero, A., Clark, T.E., Marcellino, M., 2018. Measuring uncertainty and its impact on the economy. *The Review of Economics and Statistics* 100, 799–815. doi:10.1162/rest_a_00693.
- Cebreros, A., Salcedo, A., Chiquiar, D., Heffner-Rodríguez, A., 2020. Trade Policy Uncertainty and its Effect on Foreign Direct Investment: Evidence from Mexico. Working Papers 2020-14. Banco de México. URL: <https://ideas.repec.org/p/bdm/wpaper/2020-14.html>.
- Dahlhaus, T., Vasishtha, G., 2014. The Impact of U.S. Monetary Policy Normalization on Capital Flows to Emerging-Market Economies. Staff Working Papers 14-53. Bank of Canada. URL: <https://ideas.repec.org/p/bca/bocawp/14-53.html>.
- Forbes, K.J., Warnock, F.E., 2012. Capital flow waves: Surges, stops, flight, and retrenchment. *Journal of International Economics* 88, 235–251. doi:10.1016/j.jinteco.2012.03.006.

- Fratzscher, M., 2012. Capital flows, push versus pull factors and the global financial crisis. *Journal of International Economics* 88, 341–356. URL: <https://ideas.repec.org/a/eee/inecon/v88y2012i2p341-356.html>.
- Gauvin, L., McLoughlin, C., Reinhardt, D., 2013. Policy uncertainty spillovers to emerging markets - evidence from capital flows. *SSRN Electronic Journal* doi:10.2139/ssrn.2273452.
- Gelos, G., 2019. Capital flows at risk : taming the ebbs and flows. International Monetary Fund, Washington, D.C.
- Gourio, F., Siemer, M., Verdelhan, A., 2015. Uncertainty and international capital flows. *SSRN Electronic Journal* doi:10.2139/ssrn.2626635.
- Hansen, B.E., 1996. Inference when a nuisance parameter is not identified under the null hypothesis. *Econometrica* 64, 413. doi:10.2307/2171789.
- Hernandez-Vega, M., 2017. Portfolio Investment and U.S. Monetary Policy Announcements: an event study analysis using high frequency data from Mexico. Working Paper Series 2017-02. Banco de Mexico.
- Ibarra, R., Tellez-Leon, I.E., 2019. Are all types of capital flows driven by the same factors? evidence from Mexico. *Empirical Economics* 59, 461–502. doi:10.1007/s00181-019-01624-5.
- Jackson, L.E., Kliesen, K.L., Owyang, M.T., 2019. The nonlinear effects of uncertainty shocks. *Studies in Nonlinear Dynamics & Econometrics* 24. doi:10.1515/sn-de-2019-0024.
- Jotikasthira, C., Lundblad, C., Ramadorai, T., 2012. Asset Fire Sales and Purchases and the International Transmission of Funding Shocks. *Journal of Finance* 67, 2015–2050. URL: <https://ideas.repec.org/a/bla/jfinan/v67y2012i6p2015-2050.html>.
- Jurado, K., Ludvigson, S.C., Ng, S., 2015. Measuring uncertainty. *American Economic Review* 105, 1177–1216. doi:10.1257/aer.20131193.
- Koop, G., Pesaran, M., Potter, S.M., 1996. Impulse response analysis in nonlinear multivariate models. *Journal of Econometrics* 74, 119–147. doi:10.1016/0304-4076(95)01753-4.
- Lo Duca, M., 2012. Modelling the Time Varying Determinants of Portfolio Flows to Emerging Markets. Working Paper Series 1468. European Central Bank. URL: <https://ideas.repec.org/p/ecb/ecbwps/20121468.html>.
- Miranda-Agrippino, S., Rey, H., 2015. US Monetary Policy and the Global Financial Cycle. NBER Working Papers 21722. National Bureau of Economic Research, Inc. URL: <https://ideas.repec.org/p/nbr/nberwo/21722.html>.
- Mumtaz, H., Theodoridis, K., 2017. The changing transmission of uncertainty shocks in the u.s. *Journal of Business & Economic Statistics* 36, 239–252. doi:10.1080/07350015.2016.1147357.

- Rey, H., 2015. Dilemma not Trilemma: The Global Financial Cycle and Monetary Policy Independence. CEPR Discussion Papers 10591. C.E.P.R. Discussion Papers. URL: <https://ideas.repec.org/p/cpr/ceprdp/10591.html>.
- Schmidt, J., 2019. Country risk premia, endogenous collateral constraints and non-linearities: A threshold var approach. Mimeo.
- Shin, M., Zhong, M., 2018. A new approach to identifying the real effects of uncertainty shocks. *Journal of Business & Economic Statistics* 38, 367–379. doi:10.1080/07350015.2018.1506342.

A Appendix

Table A.1: Summary Statistics

	Units	Mean	Std. Deviation
Flow Variables			
Equity	USD billions	31.92	413.03
Debt Securities	USD billions	146.69	518.39
Mexico Variables			
US/Peso Exchange Rate (FX)	USD/MXN	14.82	3.47
Industrial Production (IP)	Index	99.51	5.05
Interest Rate (i)	Percentage	5.61	1.80
Stock Market Index (SM)	Index	37581.73	8726.67
US Variables			
Industrial Production (IP^*)	Index	101.63	5.47
Interest Rate (i^*)	Percentage	1.28	1.68
Uncertainty Variable			
VIX (Z)	Index	19.45	8.87
Observations		163.00	163.00

Source: EPFR, Bloomberg and Haver Analytics.

B Appendix

Table B.1: Unit Root Tests

	Aug. Dickey-Fuller	Phillips-Perron
Flow Variables		
Equity	-8.01*** (0.00)	-7.94*** (0.00)
Debt Securities	-9.17*** (0.00)	-9.27*** (0.00)
Mexico Variables		
FX growth rate	-12.45*** (0.00)	-12.46*** (0.00)
IP in log differences	-12.56*** (0.00)	-13.61*** (0.00)
SM in log differences	-12.22*** (0.00)	-12.28*** (0.00)
US Variables		
<i>IP*</i> in log differences	-9.92*** (0.00)	-9.25*** (0.00)
Uncertainty Variable		
VIX	-4.41*** (0.00)	-4.46*** (0.00)

Under the null hypothesis there is a unit root.

P-values in parenthesis. * significant at 10% ** significant at 5% *** significant at 1%.

C Appendix

Table C.1: High Uncertainty Events from January 2007 to July 2020

Date	Description
February 2007	Mortgage Lenders Network files for Chapter 11 bankruptcy becoming one of the largest casualties among subprime lenders as the US housing market slows
June 2007	Bear Stearns announces that it is shoring up its High-Grade Structured Credit Fund
July 2007	Moody's and S&P downgraded hundreds and then thousands of RMBS and CDO ratings, causing the rated securities to lose value and become much more difficult to sell, and leading to the subsequent collapse of the RMBS and CDO secondary markets
August 2007	It became apparent by August 2007 that the financial market could not solve the subprime crisis and the problems spread beyond the US's borders. The interbank market froze completely, largely due to prevailing fear of the unknown amidst banks
January 2008	The Fed slashes its target for the federal funds rate 75 basis points to 3.5 per cent, then again to three per cent as the realisation of a crisis in the housing market hits home
September 2008	Lehman Brothers bankruptcy
October 2008	Global Financial Crisis begins
May 2010	Troika (IMF/EU/ECB) stability loan package for Greece
July 2011	US debt ceiling debate
August 2011	US debt ceiling debate
September 2011	US debt ceiling debate continues
May 2012	Elections in Greece go to a second round
May 2013	Taper Tantrum by Bernanke: "In the next few meetings, we could take a step down in our pace of purchase"
June 2013	Bernanke's press conference: "If we see continued improvement and we have confidence that that is going to be sustained, then in the next few meetings, we could take a step down in our pace of purchase"
January 2014	US government shutdown begins
July 2014	US sanctions Russia over Ukraine conflict
December 2014	Oil prices fall drastically from an average of 80 USD in November to an average of 63 USD
June 2015	Chinese stock market crashes

Continued on next page

Table C.1 – continued from previous page

Date	Description
August 2015	Yuan depreciates 3 percent. After years of accommodative monetary policy from the Federal Reserve, Janet Yellen makes it clear that the Fed will raise rates soon
January 2016	Oil prices fall beyond the 27 USD per barrel
October 2016	US presidential elections
January 2018	Volpocalypse takes place: a significant pressure in the market to acquire S&P 500 options caused the liquidity of VIX futures to evaporate driving prices up dramatically
February 2018	Volpocalypse strengthens
March 2018	Tariffs on aluminum and steel are announced by President Trump
October 2018	US-China trade tensions intensify
December 2018	US-China trade tensions remain high, Federal Reserve policy normalization, and increasing concerns about a partial shut-dow
May 2019	US President Trump threatens to impose 5% tariffs to all products from Mexico. He also carried out his threat to raise import tariffs on \$200bn worth of Chinese goods from 10 percent to 25 percent. China announced plans to retaliate against the move with tariffs of up to 25 percent on nearly \$60bn of American goods
August 2019	Trump announces 10% tariffs on \$300 billion worth of Chinese imports, after two days of talks with no progress
Jan to March 2020	COVID-19

Source: Bloomberg.

D Appendix

Figure D.1: Lag Information Criteria

Lag Order Selection Criteria Bonds VAR

Endogenous variables: VIX USIP IUS FX MXIP I BONDS

Sample: 2006M01 2020M07

*Note: selection calculation does not impose restricted VAR coefficient restrictions

Lag	LogL**	LR	FPE	AIC	SC	HQ
0	- 3,349.55	NA	182,000.00	41.18	41.32	41.24
1	- 2,503.75	1,608.57	103,091.00	31.41	32.47 *	31.84 *
2	- 2,405.59	178.24	56,576.40 *	30.80 *	32.80	31.61
3	- 2,358.09	82.19	58,083.33	30.82	33.75	32.01
4	- 2,316.23	68.82	64,372.06	30.91	34.76	32.48
5	- 2,285.29	48.21	82,378.94	31.13	35.92	33.07
6	- 2,247.79	55.22	98,498.83	31.27	36.99	33.59
7	- 2,212.31	49.20	122,643.30	31.44	38.08	34.14
8	- 2,184.02	36.78	170,080.10	31.69	39.27	34.77
9	- 2,141.92	51.14	203,810.80	31.78	40.28	35.23
10	- 2,079.43	70.55 *	195,636.90	31.61	41.05	35.44
11	- 2,024.95	56.81	214,472.20	31.55	41.91	35.75
12	- 1,977.97	44.97	268,724.20	31.57	42.86	36.16

Lag Order Selection Criteria Equity VAR

Endogenous variables: VIX USIP IUS FX MXIP I EQUITY

Sample: 2006M01 2020M07

*Note: selection calculation does not impose restricted VAR coefficient restrictions

Lag	LogL**	LR	FPE	AIC	SC	HQ
0	- 3,326.23	NA	136,000.00	40.90	41.03	40.95
1	- 2,483.01	1,603.67	79,929.75	31.15	32.22 *	31.59 *
2	- 2,405.52	140.72	56,523.22	30.80	32.80	31.61
3	- 2,355.65	86.27	56,371.03 *	30.79 *	33.72	31.98
4	- 2,315.84	65.46	64,063.87	30.91	34.76	32.47
5	- 2,285.39	47.45	82,472.66	31.13	35.92	33.08
6	- 2,250.52	51.34	101,848.20	31.31	37.02	33.63
7	- 2,217.03	46.43	129,962.00	31.50	38.14	34.19
8	- 2,190.17	34.93	183,403.70	31.77	39.34	34.84
9	- 2,147.34	52.02	217,826.00	31.84	40.35	35.30
10	- 2,083.57	71.99 *	205,834.70	31.66	41.10	35.49
11	- 2,043.92	41.35	270,677.40	31.78	42.14	35.99
12	- 2,004.76	37.48	373,322.30	31.90	43.19	36.48

* indicates lag order selected by the criterion

LR: sequential modified LR test statistic (each test at 5% level)

FPE: Final prediction error

AIC: Akaike information criterion

SC: Schwarz information criterion or BIC

HQ: Hannan-Quinn information criterion

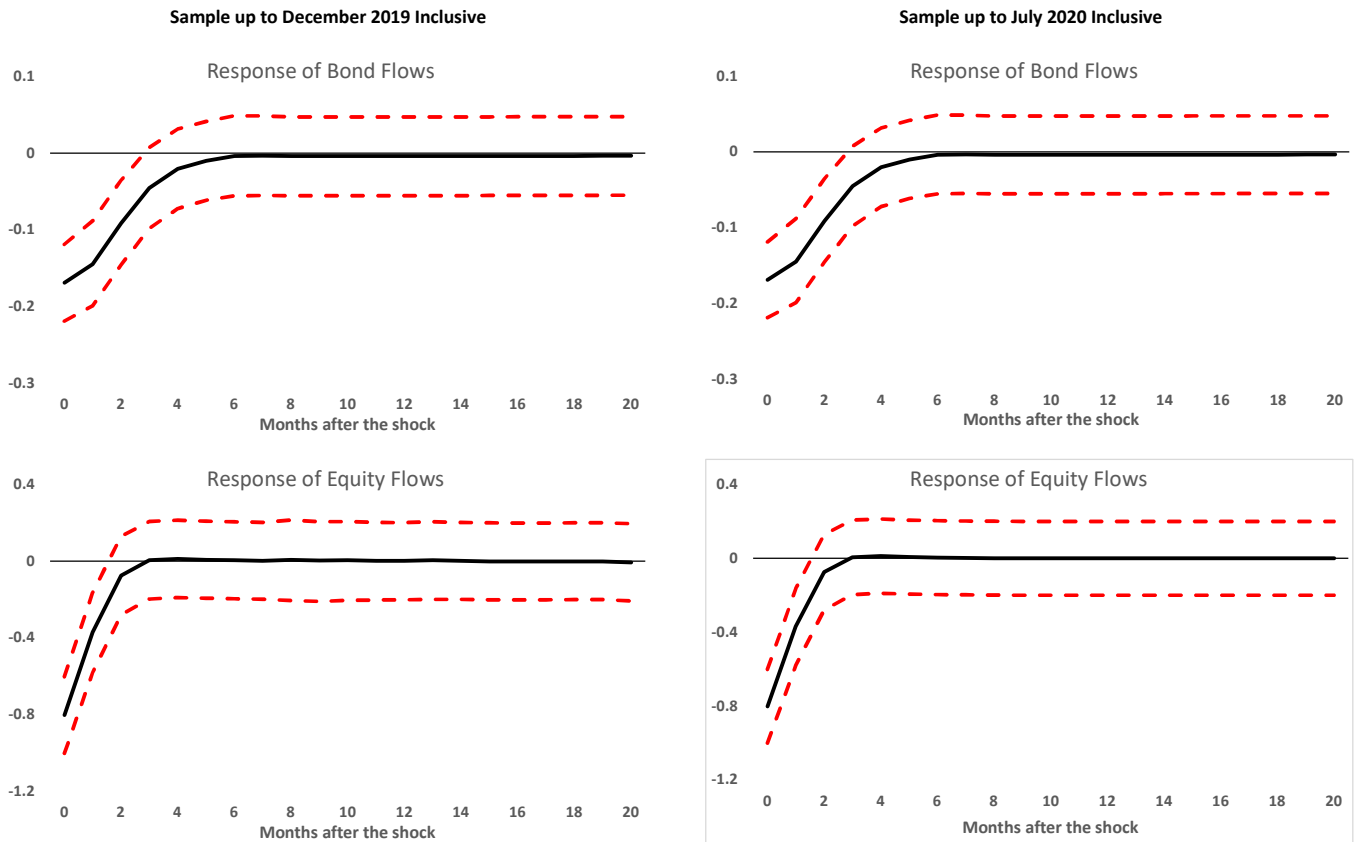
E Appendix

The GIRFs are computed as follows:

1. Chose a history Ω_{t-1}^r where $r = 1, \dots, R$ where the history is just the actual lagged value of the variables in the model at a specific date r . This implies that the number of histories is the number of observations in each regime.
2. Having the estimated residuals ε from equation 2, we use bootstrap sampling to simulate residuals (u).
3. Taking the chosen history Ω , the simulated residuals u and the estimated model parameters then simulate the evolution of all endogenous variables over k periods. Then, we obtain $Z_{t+k}(u_t, \Omega_{t-1})$, $X_{t+k}(u_t, \Omega_{t-1})$ and $Y_{t+k}(u_t, \Omega_{t-1})$ needed to calculate the unconditional expectation in equation 3.
4. To obtain the conditional expectations it is needed to add the shock of size δ to the i^{th} variable. Then we simulate the evolution of all endogenous variables over k periods and obtain $Z_{t+k}(\delta_t, u_t, \Omega_{t-1})$, $X_{t+k}(\delta_t, u_t, \Omega_{t-1})$ and $Y_{t+k}(\delta_t, u_t, \Omega_{t-1})$
5. Steps 2 to 4 are repeated B times (where $B = 10000$) to get B estimates for each regime. Then compute the average difference between these estimates. This average is also an estimate of the expected value of Z , X , and Y given the history Ω_{t-1} .
6. Repeat steps 1 to 5 R times; i.e., for all possible histories within each regime so that we obtain R estimates of $\frac{1}{B} \sum Z_{t+k}(\delta_t, u_t, \Omega_{t-1})$, $\frac{1}{B} \sum X_{t+k}(\delta_t, u_t, \Omega_{t-1})$ and $\frac{1}{B} \sum Y_{t+k}(\delta_t, u_t, \Omega_{t-1})$ as well as $\frac{1}{B} \sum Z_{t+k}(u_t, \Omega_{t-1})$, $\frac{1}{B} \sum X_{t+k}(u_t, \Omega_{t-1})$ and $\frac{1}{B} \sum Y_{t+k}(u_t, \Omega_{t-1})$.
7. Averaging these estimates over all histories, we obtain the GIRFs for a given regime.

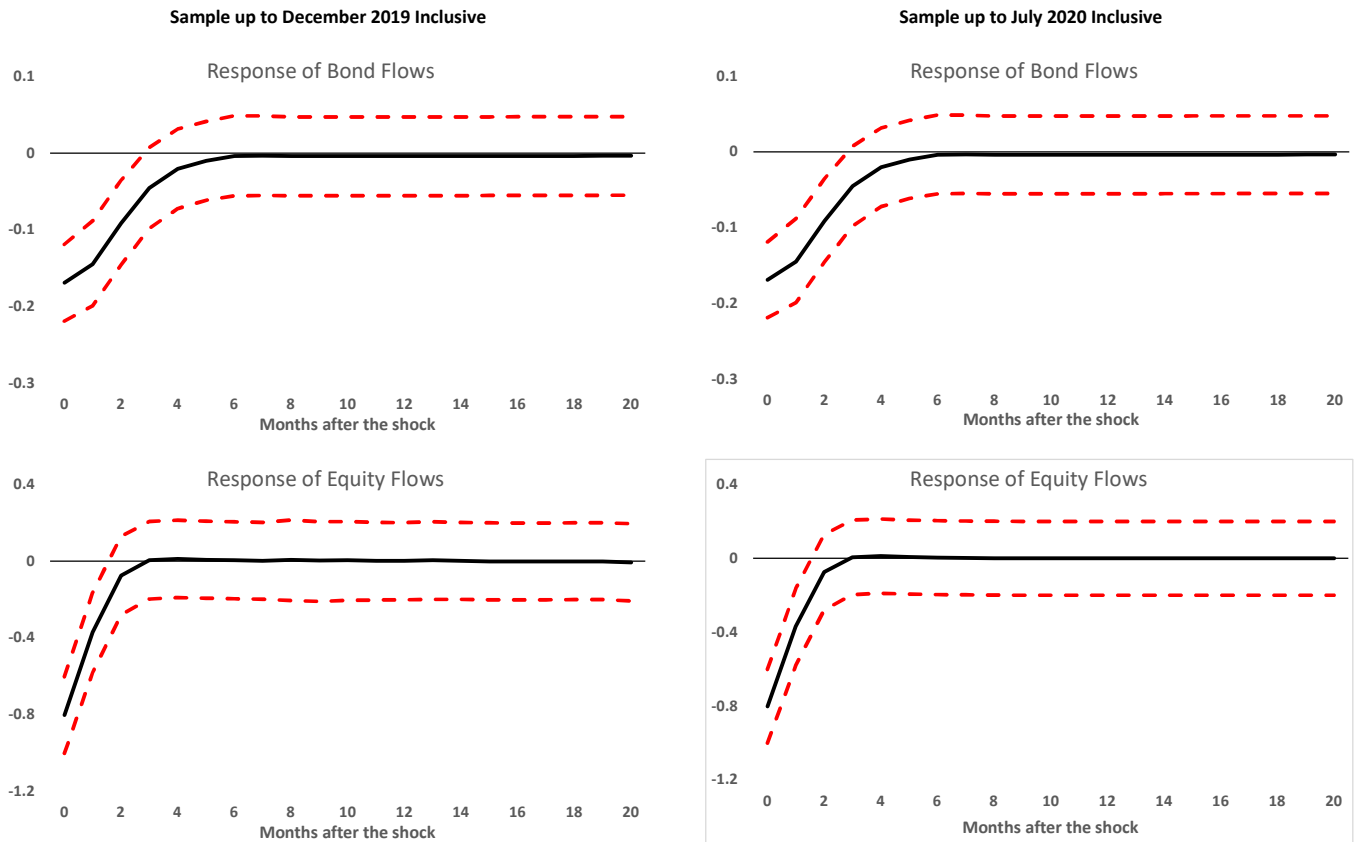
F Appendix

Figure F.1: Robustness of GIRFs to Sample Size



G Appendix

Figure G.1: GIRFs with EPU as Uncertainty Measure



H Appendix

Figure H.1: GIRFs with IGAE as Mexico's Economic Activity Indicator

