US uncertainty shocks, credit, production, and prices: The case of fourteen Latin American countries

Working paper

March 2023

Carlos Giraldo Iader Giraldo-Salazar Jose E. Gomez-Gonzalez Jorge M. Uribe



US uncertainty shocks, credit, production, and prices: The case of fourteen Latin American countries

Carlos Giraldo*
lader Giraldo-Salazar**
Jose E. Gomez-Gonzalez***
Jorge M. Uribe

Abstract

The extant literature has examined the impact of United States' uncertainty shocks on developed and large emerging market economies. However, this research has not accounted for global cycles in production, credit, and prices, which can influence the estimates of the effects of US uncertainty on the rest of the world. The effects of uncertainty in highly indebted emerging open economies, which depend heavily on US financial and real conditions, have not been studied. We analyze the effects of uncertainty shocks on 14 Latin American countries (LACs) of various sizes and various levels of dependence on US financial and real flows. Latin America is a highly indebted and heterogeneous region that is particularly sensitive to US economic and financial conditions, particularly uncertainty, in its various dimensions: real, financial, and policy related (including monetary policy). Our results show that the effects of real and financial uncertainty are more significant and long lasting than the effects of economic and monetary policy uncertainty, as measured by the use of uncertainty-related key words. All forms of uncertainty have a larger and more persistent impact on the gross domestic product of countries than the impact on credit and prices. In general, uncertainty in the US depresses economic activity in Latin America, although there is significant heterogeneity in the effects, which warrants detailed analysis of individual countries when considering policy implementation and portfolio diversification.

Key words: macroeconomic uncertainty, financial uncertainty, policy uncertainty; global business cycles; Latin America

JEL Codes: D80, E44, F21, F44, G15, O54

^{*} Latin American Reserve Fund. cgiraldo@flar.net

^{**} Latin American Reserve Fund. <u>igiraldo@flar.net</u>

^{***} Lehman College, City University of New York. jose.gomezgonzalez@lehman.cuny.edu

^{****} Universitat Oberta de Catalunya. juribe@uoc.edu

Content

I.	Introduction	4
2.	Uncertainty, investment and output	6
3.	Methodology 3.1. Uncertainty shocks 3.2. Global factors 3.3. Identification of uncertainty shocks in small open economies	8 8
4.	Data	11
5.	Results 5.1. Outputs 5.2. Credit 5.3. Prices 5.4. Correlation between uncertainty effects in credit, production and prices 5.5. Exploratory analysis of the cluster factor for uncertainty effects	13 14 18 22 26 27
6.	Conclusions	29
	References	31
	Appendix	35

1. Introduction

The effect of aggregate uncertainty on real and financial markets has recently attracted a great deal of attention in academic and policy circles¹. Uncertainty, especially its bad and unexpected components (Segal *et al.*, 2015; Berger *et al.*, 2020; Uribe and Chuliá, 2023), has a negative impact on investment, consumption, and growth. On some occasions, this is followed by a rebound (positive) effect after the uncertainty is realized (Bloom, 2009; Bloom *et al.*, 2018). Interestingly, the response of real and financial variables may be different if financial uncertainty shocks are considered (Ludvigson *et al.*, 2021).

More effort is still necessary, however, to better understand the propagation of US uncertainty shocks to other countries, especially to emerging market economies. Research in this direction is relevant for at least two reasons. First, uncertainty exerts considerable influence on credit dynamics and, therefore, on the dynamics of economic activity in general. During booms, as banks are optimistic about the ability of firms to repay their debt, they tend to lower their creditworthiness standards and extend more loans. The underlying credit boom leads to more investment, higher growth, and more lending. The opposite happens during economic downturns. Pessimism about the future capacity of firms to validate their loans induces banks to curtail firms' credit. In fact, credit crunches occur during periods of extreme pessimism with respect to future economic performance (Wisniewski and Lambe, 2013; Mehrotra and Sergeyev, 2021). Constraints for lending are generally not created by deposit shortages but by the unwillingness of banks to lend in moments of high uncertainty. Uncertainty can therefore play a major role in shaping financial and economic outcomes.

Second, as emphasized by Bhattarai et al. (2020), policy makers in emerging market economies (EMEs) often attribute both downward revisions of their economic forecasts and increased volatility in international capital flows to increases in US uncertainty. In fact, fluctuations in US uncertainty can have significant policy implications for EMEs beyond the direct negative spillover effects they generate. The effects may drive the global financial cycle similarly to the way in which the Federal Reserve's monetary policy does. For EMEs, the traditional open economy policy "trilemma", the idea that countries cannot have independent monetary policy, perfect capital mobility, and flexible exchange rates simultaneously, may have become an "irreconcilable duo", according to which independent monetary policies are possible if and only if the capital account is managed (Rey, 2018).

See for instance Bloom (2009), Bachmann et al. (2013), Jurado et al. (2015), Baker et al. (2016), Bordo et al. (2016), Chuliá et al. (2017), Nakamura et al. (2017); Berger et al. (2020), Carriero et al. (2021), Ludvigson et al. (2021), Caldara and Iacoviello (2022), among many others.

Arguably, Latin America has been the most crisis-prone region in the world in the face of international shocks over the past decades, as illustrated by the balance-of-payment crisis in the 1980s and several banking crises in the 1990s (Canova, 2005; Garcia-Herrero, 2021). A perverse combination of a weak institutional environment, significant corruption, poorly developed financial markets, and high public debt burdens could be at the core of the explanation of why relatively mild shocks arising in the US can have such a strong impact on Latin American countries (LACs). However, countries in the region are highly heterogeneous from institutional, macroeconomic, and financial perspectives. Therefore, a better understanding of the transmission of a varied range of US shocks to several LACs contributes to the international finance literature dealing with spillovers, contagion, and international shock transmission.

We contribute to this literature by expanding the analysis of the effects of US uncertainty shocks on 14 LACs. To support our claims, we use natural identifying restrictions for US uncertainty shocks and a recently constructed and comprehensive dataset comprising time series for credit, output, and prices of 51 world economies. In the empirical analysis, we employ uncertainty indicators recently developed in the macroeconomics literature, which aim to properly differentiate uncertainty from related notions such as volatility, risk, or risk aversion (Jurado et al., 2015; Baker et al., 2016, Husted et al., 2020; Ludvigson et al., 2021). Moreover, our emphasis on Latin America, one of the most indebted regions in the world and, therefore, particularly sensitive to current uncertainty regarding the monetary policy of the Fed or economic policy uncertainty in the US, has been absent from the literature thus far. The countries in our dataset are analyzed here for the first time along the four dimensions of uncertainty that we propose (i.e., economic policy, monetary policy, macrofinancial, and real uncertainty).

This paper differs from previous studies investigating the effects of US uncertainty shocks on real and financial variables in other countries (e.g., Mumtaz and Theodoridis, 2017; Belke and Osowski 2019; Bonciani and Ricci, 2020; Gomez-Gonzalez et al., 2020; Cuaresma et al., 2020; Cesa-Bianchi et al., 2020), as we study the case of small open economies, which arguably do not contemporaneously affect the uncertainty dynamics of the US economy. Unlike previous studies that do include emerging market economies (e.g., Bhattarai et al., 2020; Rivolta and Trecroci, 2020; Belke and Osowski, 2019), we focus on the role of credit markets in the transmission of uncertainty, and we also consider the distinct (but complementary) roles of real, financial, and economic policy uncertainty (including monetary policy uncertainty). Another distinctive feature of our work is that we explicitly consider the global factors that drive credit, production and price cycles around the world and that might "contaminate" the effect of US uncertainty shocks on the rest of the world, as estimated in the previous literature.

Our perspective is comparative. We focus on fourteen LACs: Argentina, Bolivia, Brazil, Chile, Colombia, Costa Rica, Ecuador, El Salvador, Guatemala, Honduras, Mexico, Peru, Paraguay, and Uruguay, a highly heterogeneous

group of countries according to their degree of financial openness, with varying degrees of commercial and financial dependence on the US (including dollarization), and with different institutional frameworks.

We use the theoretical order of contemporaneous exogeneity that our setting allows for identification. As recently highlighted by Kilian *et al.* (2022), in very rare cases in macroeconomics, recursive ordering in a VAR system is naturally supported by theoretical considerations to identify a shock. This makes the identification of uncertainty shocks at the national level extremely challenging since it is not possible to claim that uncertainty is contemporaneously exogenous (or endogenous) to other macroeconomic aggregates in the system. We depart from this literature, as we estimate the effects of US uncertainty on a set of small open economies, and place uncertainty first in our VAR system. Therefore, US uncertainty is assumed to be contemporaneously exogenous to domestic variables in LACs, consisting of credit, gross domestic product (GDP) and prices. In addition, before estimation, we remove the part of US uncertainty shocks that can be attributed to general global cycles, thus guaranteeing that only the direct effect of US uncertainty is accounted for in our estimations.

Our main findings indicate that the responses of credit, GDP, and prices in LACs countries to US uncertainty shocks are highly heterogeneous, depending on the country and the specific type of shock. Responses are not easily clustered according to country characteristics. For instance, responses do not systematically depend on country size, level of financial development, level of connectedness with the US economy, degree of dollarization, or subregion within LACs. This result indicates that policy implementation and the design of portfolio diversification strategies, when faced with US uncertainty shocks, merit research effort at the national level.

An interesting result is that output responds more strongly to US uncertainty shocks than credit in LACs countries. In fact, output in the majority of countries responds negatively and significantly, while the response of credit is negative for only a small number of countries. Additionally, the duration of the response of credit tends to be shorter compared to the duration of the response of output. This fact implies that the transmission of US uncertainty shocks to Latin America seems to be explained more by trade and investment channels than by financial channels. This result contrasts with those of Gomez-Gonzalez *et al.* (2020), who show that credit and stock markets are important transmission channels of US uncertainty shocks to real variables in developed economies. This can be explained by the fact that financial markets in LACs are not well developed and their degree of integration with US financial markets is relatively low. Prices in Latin America respond mainly to US real uncertainty prices, as well.

2. Uncertainty, investment and output

The main approach to understanding the effects of uncertainty in macroeconomic systems has been shaped by the literature on irreversible investment, which views a company's future investments as real options and highlights the importance of waiting until uncertainty is realized before carrying out actual investment, hence emphasizing the value option generated by uncertainty shocks and the firm's ability to postpone the realization of investment projects. This paradigm implies that large uncertainty shocks lead to decreased investment and potentially decreased employment, ultimately causing a decline in overall economic activity. This has been supported by numerous studies following the seminal work by Bernanke (1983) (e.g., Bertola and Caballero 1994, Abel and Eberly 1996, Leahy and Whited 1996, Caballero and Pindyck 1996, Bloom et al 2007, or more recently, Bloome et al., 2018, Panagiotidis and Printzis 2021, Chortareas and Noikokyris, 2021).

Studying the effects of uncertainty on aggregate economic decision-making has recently regained interest among scholars (e.g., Stokey, 2008; Bloom, 2009; Jurado *et al.*, 2015; Baker *et al.*, 2016; Bordo *et al.*, 2016; Ludvigson *et al.*, 2021). The main motivation has been the wide consensus that a major cause of the Global Financial Crisis of 2008-10 was the perverse combination of uncertainty and externalities in the financial system. The growing interest in a better understanding of uncertainty and its effects on real and financial outcomes has led to the development of an extensive body of literature challenging the conventional idea that risk and uncertainty are interchangeable terms. In particular, new indicators for measuring uncertainty based on text mining (Baker *et al.*, 2016) and big data (Jurado *et al.*, 2015) have been developed.

While most psychologists and behavioral economists take the rational agent model of equilibrium-based economic theory as their point of departure, hard-to-rationalize decisions made by banks and global investors before and during financial crises have motivated a renewed interest in studying Keynesian "animal spirits" that emerge in turbulent times (Akerlof and Shiller, 2009; Berardi, 2022). This has been frequently done within the new behavioral economics framework, which uses neuroscience to help economists understand the behavior of agents in real-world experimental situations (Sent, 2004). The main aim is to understand and predict behaviors which challenge the predictions of theoretical models relying on rationality axioms of individual behavior.

Uncertainty is not equivalent to risk. In the real world, the production of goods takes time. The payoff associated with an action is separated from the moment of choice by some period of calendar time (Davidson, 1991; Brandolini *et al.*, 2011; Istiak and Serletis, 2020). In the real world, true uncertainty is not captured by the objective or subjective probabilities with which individuals make decisions on risky alternatives. In a true uncertainty environment, even when objective relative frequencies have existed in the past or subjective probabilities exist today, the decision-maker believes that during the calendar time elapsed between the moment of the decision and the payoff, unforeseeable changes may occur. In this type of environment, the availability of funding sources and "animal spirits" are the driving forces of investment, and banking credit is the key link between investment projects and the beginning of production processes.

In this paper, we study the effect of various kinds of US uncertainty shocks on credit, output, and other variables for a set of Latin American countries. We add to the literature that studies the effects of large uncertainty shocks at the international level by taking advantage of the natural identifying restrictions that emerge in our setting of small open economies highly indebted and dependent on US financial and real conditions. We also contribute to the design of policy in emerging market economies, some of which are considered here for the first time when analyzing uncertainty shocks. None of them have been explored before from the four uncertainty perspectives that we consider in what follows.

3. Methodology

Our methodology consists of two parts. First, we use dynamic factor models (DFM) and a large dataset covering 51 countries to create global factors based on credit, production, and price information. These factors enable us to create "clean" uncertainty indicators for the US, which remove the influence of global shocks that are not caused by the US economy and may impact the credit, prices, and economic activity of LACs. Next, we use these clean uncertainty indicators in single-country VAR systems to evaluate the impact of US uncertainty on credit, GDP, and inflation in LACs, placing uncertainty first (exogenous) in the corresponding VAR.

3.1. Uncertainty shocks

We use four different proxies for uncertainty in the US economy, which measure different facets of the phenomenon: the real and financial uncertainty indicators developed by Jurado *et al.* (2015) and Jurado *et al.* (2021); the economic policy uncertainty index of Baker *et al.* (2016) and the monetary policy uncertainty by Husted *et al.* (2020). These uncertainty proxies may react to global economic cycles in prices, credit and economic activity. Hence, we must remove the effects of such global factors on our uncertainty proxies before estimating the effects on LACs. To this end, we resort to a dynamic factor model (DFM), explained in the next section.

3.2. Global factors

Let us start by considering a parsimonious representation of our system, consisting of a large number of series of credit, GDP and prices for the global economy, in terms of k factors. Here, s = 1, ..., S, refers to the S = 153 series in our system (three for each of the N = 51 countries). Each series, x, can be expressed as in the following equation:

$$X_{ct} = \lambda_{1c} F_{1t} + \cdots + \lambda_{kc} F_{kt} + U_{ct}, \tag{1}$$

where x_{st} is a series of either credit, GDP or prices for a given country at period t and it depends on the exposure of such series to k factors, $\{F_{1t},...,F_{kt}\}$, and on an idiosyncratic component, u_{st} . We note that factors only change

over time, so they are common to all series and represent underlying global economic forces (*i.e.*, global cycles of prices, credit or economic activity). The exposure of each series is nonetheless diverse, as highlighted by the fact that the factor loads $\{\lambda_{7s},...,\lambda_{ks}\}$ change across series (although they do not change in time). As we said before, u_{st} represents shocks that affect only series x_{st} . These shocks are usually assumed to be white noise.

The model stated in (1) can be rewritten in its static form simply by redefining the vector of factors to contain the dynamic factors and their lags and the matrix of loads accordingly, as follows:

$$\begin{array}{l}
X & AF & U \\
(S \times T) = (S \times r)(r \times T) + (S \times T),
\end{array}$$
(2)

where $X = (X_{\gamma}...,X_{S})$ and $F = (F_{\gamma}....,F_{T})$. F and Λ are not identifiable, we require further restrictions. That is, for any arbitrary $(r \times r)$ invertible matrix H, $F\Lambda' = FHH^{-1}\Lambda' = F^*\Lambda'^*$, where $F^* = F\Lambda$ and $\Lambda^* = \Lambda H^{-1}$, the factor model is observationally equivalent to $X = F^*\Lambda'^* + u$. Therefore, r^2 restrictions are required to uniquely fix F and Λ (Bai and Wang, 2015). We note that the estimation of the factors by principal components analysis (PCA) or singular value decomposition (SVD) imposes the normalization that $\frac{\Lambda' \Lambda}{N} = I_r$ and F'F are diagonal. These two are sufficient to guarantee identification up to a column sign rotation, meaning that the factors may have any sign. We can fix the sign according to economic intuition, but this is irrelevant for the identification of the uncertainty shocks.

There are hundreds of factors that could in principle affect the series of credit, GDP and prices in the equation (e.g., interest rates, fuel prices, weather, risk aversion, etc.). In our data-driven framework, we circumvent this problem by assuming the factors in Equations 1 or 2 as unobservable and unknown, so we need to recover them from the data. Herein, the total number of informational series included in the factor estimations, X_{r} is S, and this set accounts for all available variables for all countries in the original dataset, not only for those countries analyzed. In this way, we guarantee a sufficiently high number of series to recover the unknown factors using more accurately PCA. The number of factors is determined by using the criterion proposed by Bai and Ng (2007).

In the second step, factors are added to the individual country's systems. This is done by taking the residuals of a linear projection of uncertainty indices described in section 3.1., U_t onto F_t , and labeling the residuals of these regressions as the estimated (orthogonalized) uncertainty \hat{U}_t , shocks.

3.3. Identification of uncertainty shocks in small open economies

A traditional VAR representation of a domestic economy is given in its reduced form by the following set of equations:

$$\mathbf{Y}_{it} = A_{i}(L)\mathbf{Y}_{it} + \mathbf{e}_{it} \tag{3}$$

where \mathbf{Y}_{it} is a $(M \times 1)$ vector that contains M - 1 domestic variables in the model for each country, i = 1,...N, plus the uncertainty indicator, which is common to all countries. $\mathbf{A}_{i}(\mathbf{L})$ is a lag-operator polynomial of order d, and \mathbf{e}_{it} is a vector of reduced-form residuals for country i. The M - 1 domestic series included in \mathbf{Y}_{it} are credit growth, GDP growth and inflation. Such a representation is enriched by a common factor structure provided by a US uncertainty shock that affects all countries, as constructed before.

In this context, Y_{it} can be split into two parts: the first part contains the orthogonalized uncertainty shocks, and the second part contains the domestic economy variables. Thus, the multivariate dynamics of the system (Y_{it}, U_{it}) is described by the following set of equations:

$$\begin{bmatrix} \hat{\boldsymbol{U}}_t \\ \mathbf{Y}_{it} \end{bmatrix} = \mathbf{A}_i \left(\mathbf{L} \right) \begin{bmatrix} \hat{\boldsymbol{U}}_t \\ \mathbf{Y}_{it} \end{bmatrix} + \mathbf{V}_{it} \tag{4}$$

where V_{it} is a vector of residuals with a mean equal to zero and a variance-covariance matrix given by Q_{it} . Equation 4 can be seen as a multicountry factor-augmented VAR model, where the factor corresponds to the orthogonalized uncertainty shocks in the US. That is, the factor is observable, conditional on having an appropriate proxy for uncertainty. In the next section, we show that our main results hold irrespective of the uncertainty proxy that we use.

The VAR system described in Equation 4 can be rewritten in terms of the system's innovations, V_{it} as in the following equations:

$$\begin{bmatrix} \hat{\boldsymbol{U}}_t \\ \boldsymbol{Y}_{it} \end{bmatrix} = \begin{bmatrix} \bar{\boldsymbol{U}}_t \\ \boldsymbol{Y}_{it} \end{bmatrix} + \boldsymbol{R}_i (\boldsymbol{L}) \, \boldsymbol{V}_{it} \tag{5}$$

In this case, \overline{U}_t and \overline{Y}_{it} correspond to the unconditional means of the stochastic processes, and $R_i(L)$ is a polynomial in the lag operator of infinite order. The structural (theoretical) innovations can be recovered from the system in Equation 5, imposing extraneous restrictions on the VAR representation. For instance, Sims (1980) proposed to identify the system by using a Cholesky factorization of the variance-covariance matrix in the reduced form model, Q_i , which is equivalent to defining a lower-triangular matrix \tilde{B}_i that multiplies the matrices in $R_i(L)$ and contains as many theoretical restrictions as needed to identify the system.

Kilian et al. (2022) have recently criticized the use of recursive orderings in identifying uncertainty shocks by pointing out that within a domestic economy, it is not possible to set - an order for uncertainty shocks, i.e., it is not possible to know if those shocks should be placed last or first in the system (or in any intermediate

position for that matter), as uncertainty both impacts and is impacted by all other variables simultaneously. Furthermore, Kilian *et al.* (2022) show that the practice of changing the VAR ordering to valuate for the robustness of the effects is wrong and fails to identify shocks in many cases.

We draw inspiration from this criticism for our approach, which involves identifying the effects of foreign uncertainty shocks on LACs countries by placing uncertainty first in the respective VAR system. Under the small open economy assumption of LACs with respect to the US, foreign uncertainty is considered exogenous by definition. To achieve this, we use a Cholesky factorization to construct our impulse-response functions (IRFs), as shown in Equation 6:

$$\begin{bmatrix} \mathbf{U}_{t} \\ \mathbf{Y}_{it} \end{bmatrix} = \begin{bmatrix} \overline{\mathbf{U}}_{t} \\ \mathbf{Y}_{it} \end{bmatrix} + \Phi_{i} (\mathbf{L}) \, \varepsilon_{it} \tag{6}$$

In this case, we have that $\tilde{\mathbf{B}}_{i}^{*1}\mathbf{V}_{it} = \varepsilon_{it}$ and $\mathbf{R}_{i}(\mathbf{L})\tilde{\mathbf{B}}_{i} = \Phi_{i}(\mathbf{L})$. Naturally, ε_{it} is a vector of dimensions $M \times 1$, which contains the structural innovations, and $\Phi_{i}(\mathbf{L})$ are the structural IRFs of the system. It is worth noting that we do not specify the ordering of the domestic variables, \mathbf{Y}_{it} as we are interested only in the effects of US uncertainty. Our estimates of the IRFs are indeed invariant to all possible combinations and orderings of the remaining variables. IRFs are constructed by using the MA representation of the system in equation 6, which exists under suitable stationary conditions as in any VAR model (see Lütkepohl, 2006).

By regressing uncertainty on the factors described in section 3.2 before introducing it into the VAR system, we allow uncertainty to be contemporaneously affected by global factors such as credit, economic activity, and prices. If desired, we could present our system as a factor-augmented VAR model with K factors, where the global activity factors come before uncertainty in the US. Finally, inference is conducted through bootstrapping, as our uncertainty indicators were themselves estimated in a previous step, which makes traditional inference methods inappropriate due to the possibility of measurement error.

4. Data

We estimate our models by using information on fourteen LACs with different degrees of economic development. For all of them, the US is an important source of investment, remittances, credit, and trade. Included countries are Argentina, Bolivia, Brazil, Chile, Colombia, Costa Rica, Ecuador, El Salvador, Guatemala, Honduras, Mexico, Peru, Paraguay and Uruguay. We use quarterly data spanning the period March 2000 - June 2022. Data from 2000 to December 2019 were collected from the database of Monnet and Puy (2021). We completed the dataset from 2020 to 2022 by using the same sources used by these authors.

We excluded the series of share prices and bond yields from our analysis because the quality of these data for LACs is unreliable. Additionally, firm financing in LACs occurs through domestic banking. Nonintermediate capital markets play a minor role.

To construct our global factors, we used data for 51 countries (153 series), namely, credit, GPD and price series of Argentina, Australia, Austria, Belgium, Bolivia, Brazil, Canada, Chile, Colombia, Costa Rica, Cyprus, Denmark, El Salvador, Finland, France, Germany, Greece, Guatemala, Honduras, Iceland, India, Ireland, Israel, Italy, Japan, Korea, Luxembourg, Malaysia, Malta, Mexico, Morocco, Netherlands, New Zealand, Norway, Pakistan, Peru, Philippines, Portugal, Singapore, South Africa, Spain, Sweden, Switzerland, Taiwan, Thailand, Turkey, United Kingdom, United States, Uruguay, Ecuador, and Paraguay. All variables were transformed before estimation of the DFMs and VARs by using log-differences to ensure stationarity (meaning that we work with credit growth, GDP growth and inflation rather than the variables in levels).

The panel for LACs was slightly unbalanced. In particular, there are no credit data for Bolivia in 2022:Q2, El Salvador from 2000:Q1 to 2001:Q3, Peru from 2022:Q1 to 2022:Q2, Ecuador from 2000:Q1 to 2005:Q4, and GDP for Guatemala from 2000:Q1 to 2000:Q4. Only Ecuador lacked a considerable amount of information for credit, but we opted to keep all of the countries in our analysis. We balanced the panel when using the whole dataset by imputing the missing observations with an iterative regularized PCA algorithm developed by Josse and Husson (2016)².

To gauge uncertainty, we utilized indices based on the stochastic volatilities of a large set of financial and macroeconomic variable residuals, as in Jurado *et al.* (2015) and Lugvidson *et al.* (2021), as well as word count measures, such as the Economic Policy Uncertainty (EPU) index by Baker *et al.* (2016) and the Monetary Policy Uncertainty index by Husted *et al.* (2020). The former two indices can be found on Ludvigson's web page https://www.sydneyludvigson.com/. We selected one-month-ahead measures for real and financial uncertainty and then reshaped the series by taking the observation for the end of each quarter. The latter two measures can be seen in https://www.policyuncertainty.com/.

Figure 1 shows the four proxies of uncertainty employed in our estimations. All uncertainty variables were normalized to have zero mean and unit variance before estimation to guarantee comparability across all specifications.

The iterative (regularized) PCA algorithm works as follows: a) initial values such as the mean of each variable are used to replace missing values; b) regular PCA is used the complete dataset, c) Then, reconstruction formulas (regularized) are used to impute the missing values, d) the number of components used for the imputation of missing data is calculated by cross-validation. e) Steps above are repeated until convergence to a certain threshold is achieved. We used the r-implementation in the R-package "missMDA" as of October 13 2022.

The dotted lines correspond to 2008, 2010, 2020, and 2021, and they emphasize the global financial crisis (GFC) and the COVID-19 crisis. Both were uncertainty peaks. The figure shows that monetary policy uncertainty also peaked at the beginning of the sample period during the dot-com crisis, which was accommodated by a change in the Fed's monetary policy stance. Financial uncertainty was higher during the GFC than during the COVID-19 crisis, while the opposite is true for real uncertainty. This is in line with the agreement in the profession on the differences in the nature of the two crises.

Figure A1 in the Appendix shows the estimated global factors used to purge US uncertainty from global cycles and shocks before estimation of the FAVAR models for LACs, whose results are shown in the next section.

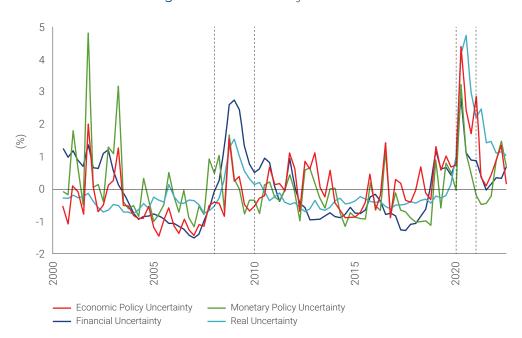


Figure 1. US Uncertainty Indicators

Note: The figure shows the four uncertainty proxies used in our study, and highlights with dotted vertical lines the global financial crisis and the COVID-19 crisis, where uncertainty peaked.

5. Results

In this section, we present our main results regarding the response of output, credit, and prices to four types of US shocks. This section is divided into three subsections, each corresponding to one of the variables for which we are evaluating the transmission of shocks.

5.1. Output

Figures 2 to 5 present the response of output in the same sample of LACs countries to the four types of US uncertainty shocks. In all four cases, the black line in each panel represents the median of the identified impulse response functions. The horizontal axis represents time, measured in quarters. The shadowed areas are confidence intervals estimated by bootstrapping (5th and 95th percentiles). The estimation period is 2000g1-2022g2.

As shown in Figure 2, output in thirteen countries responds negatively to US financial uncertainty shocks. El Salvador is the only country for which output does not respond to a US financial uncertainty shock. Interestingly, in most cases, the response is relatively persistent, between three and four quarters. The only exception is Chile, in which the negative response lasts only one quarter. This result highlights that output in LACs countries is sensitive to US financial uncertainty shocks. Noticeably, in most cases, there is no significant rebound effect. Exceptions are Bolivia, Peru, and Uruguay. The duration of the rebound, however, is short.

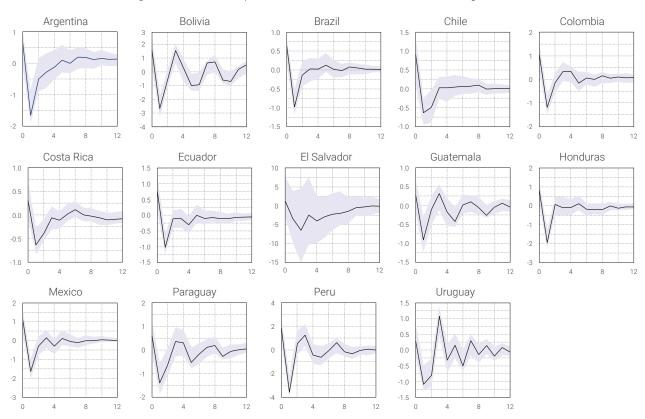


Figure 2. GDP Response to a US Financial Uncertainty Shock

Note: The figure shows the response of GDP in Latin American countries to US financial uncertainty. The shadowed area corresponds to 95% confidence intervals constructed by bootstrapping.

Importantly, output in the vast majority of the countries included in the sample responds negatively and significantly to a US financial uncertainty shock, while the response of credit is negative for only half of these countries (see section 5.2 in what follows). Additionally, the duration of the response of credit tends to be shorter compared to the duration of the response of output (see section 5.2 in what follows). This fact implies that the transmission of these shocks seems to be explained more by trade and investment channels than through financial channels. This result contrasts with those of Gomez-Gonzalez *et al.* (2020), who showed that credit and stock markets are important transmission channels of US uncertainty shocks to real variables in developed economies. This can be explained by the fact that financial markets in emerging market countries are not well developed and their degree of integration with US financial markets is relatively low (Gamba-Santamaria *et al.*, 2017).

Figure 3 depicts the response of output in LACs countries to a US real uncertainty shock. The results are qualitatively identical to those shown in Figure 2, except for Bolivia, Costa Rica, and Guatemala, countries in which there is a short rebound effect. The responses of output to US financial uncertainty shocks are, however, longer lasting than the responses of output to US real uncertainty shocks. The responses of output in individual countries to US policy uncertainty shocks are also in line with the responses of output to US financial and real uncertainty shocks, as observed from Figure 4. The immediate response is negative for all countries except for El Salvador, and short-lasting rebound effects occur in Bolivia, Mexico, Paraguay, Peru, and Uruguay.

Finally, Figure 5 shows the response of output to US monetary policy uncertainty shocks. Similarly, the immediate response of output to this shock is negative in most cases, except for El Salvador and Paraguay. A significant rebound effect occurs in Bolivia, Colombia, Guatemala, Paraguay, Peru, and Uruguay.

While the response of output to the four types of US uncertainty shocks is similar, interestingly, a significant rebound effect is more frequently observed when keyword-counting measures of US uncertainty shocks are considered. Additionally, the duration of the immediate negative response is shorter for these two types of uncertainty shocks. Together, these two results imply that when bad news regarding policy and monetary policy in the US are produced, firms in LACs respond by delaying their investment plans, leading to a reduction in output. However, as news usually dissipates quickly, investment in these countries responds quickly when uncertainty is resolved and increases significantly, leading to higher output.

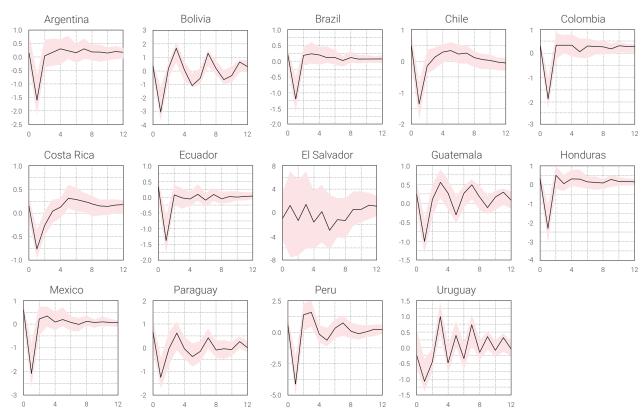


Figure 3. GDP Response to a US Real Uncertainty Shock

Note: The figure shows the response of GDP in Latin American countries to US real uncertainty. The shadowed area corresponds to 95% confidence intervals constructed by bootstrapping.

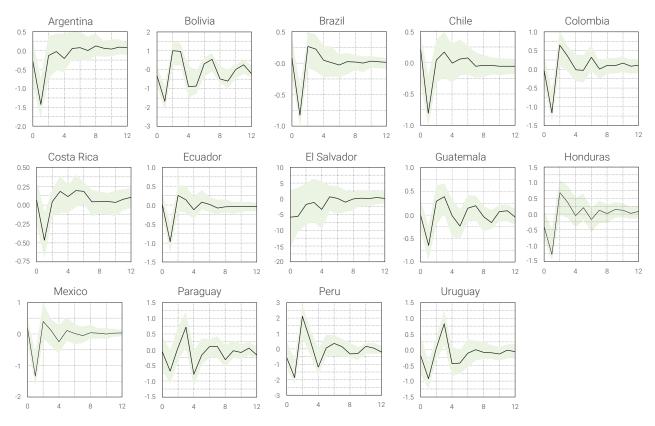


Figure 4. GDP Response to a US Policy Uncertainty Shock

Note: The figure shows the response of GDP in Latin American countries to US economic policy uncertainty. The shadowed area corresponds to 95% confidence intervals constructed by bootstrapping.

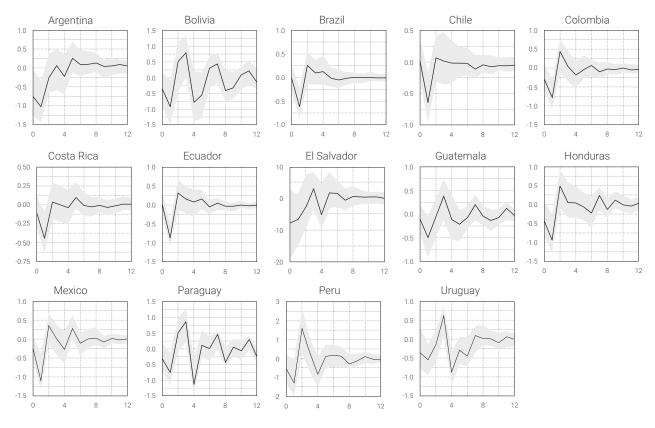


Figure 5. GDP Response to a US Monetary Policy Uncertainty Shock

Note: The figure shows the response of GDP in Latin American countries to US monetary policy uncertainty. The shadowed area corresponds to 95% confidence intervals constructed by bootstrapping.

5.2. Credit

Figures 6 to 9 depict the response of aggregate credit in 14 LACs countries to US uncertainty shocks (financial, real, policy, and monetary policy, respectively). As before, in all four cases, the black line in each panel represents the median of the identified impulse response functions. The horizontal axis represents time, measured in quarters. The shadowed areas are confidence intervals estimated by bootstrapping (5th and 95th percentiles). The estimation period is 2000q1-2022q2.

Figure 6 shows that the response of credit in the region to a US financial uncertainty shock is highly heterogeneous. Seven out of fourteen countries present a negative response. In most cases, these responses are relatively short-lived. For instance, in Argentina, the response is only significant in the second quarter after the shock, in Mexico between the fourth and sixth quarters, and in Peru between the third and fifth quarters. How-

ever, in Honduras, the response is negative immediately after the shock and lasts up to the ninth quarter. Three countries present a positive response to the financial uncertainty shock. These responses are short in all three cases and correspond to South American countries, Chile, Colombia, and Paraguay. Finally, credit in four countries (Bolivia, Brazil, Guatemala, and Uruguay) does not respond significantly to a US financial uncertainty shock.

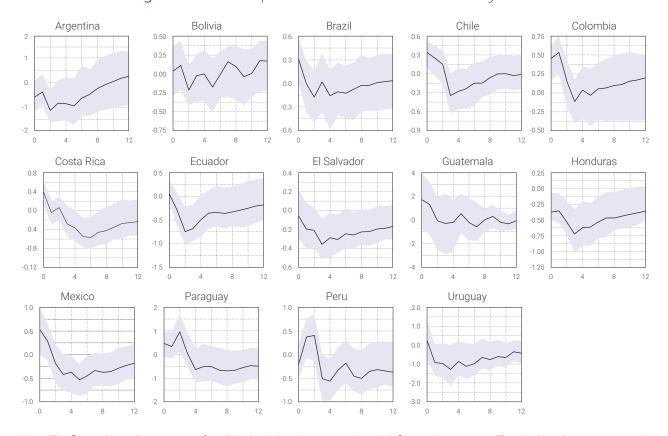


Figure 6. Credit Response to a US Financial Uncertainty Shock

Note: The figure shows the response of credit in Latin American countries to US financial uncertainty. The shadowed area corresponds to 95% confidence intervals constructed by bootstrapping.

Interestingly, responses are not easily clustered according to country characteristics. For instance, responses do not systematically depend on country size, level of financial development, level of connectedness with the US economy, degree of dollarization, or subregion within LACs. Additionally, there are no rebound effects for those countries presenting a negative response to the shock. In other words, there is no significantly positive response after the uncertainty has been resolved.

These results contrast with those of Gomez-Gonzalez et al. (2020), who showed that the response of credit in developed economies to a US financial uncertainty shock is mostly negative and more persistent than that in LACs countries. This can represent the fact that developed countries have credit markets that are more intensively connected with the US financial system, and hence, uncertainty shocks transmit more rapidly and persistently.

Figure 7 shows the responses of credit in each country to a US real uncertainty shock. Here, again, the results are heterogeneous. Interestingly, the number of countries that do not respond to real uncertainty shocks in the US is larger, nine out of fourteen (Argentina, Bolivia, Brazil, Colombia, Costa Rica, Guatemala, Honduras, Paraguay, and Uruguay). Three countries present a negative, almost immediate, and short-lived response, namely, Ecuador, El Salvador, and Mexico. Importantly, credit in these three countries also responds negatively to US financial uncertainty shocks. This can be explained by the high degree of market integration that they have with the US. However, it is important to note that not all the countries in the region that are highly integrated with the US exhibit a negative response to a US uncertainty shock. Consider, for instance, the cases of Costa Rica and Guatemala.

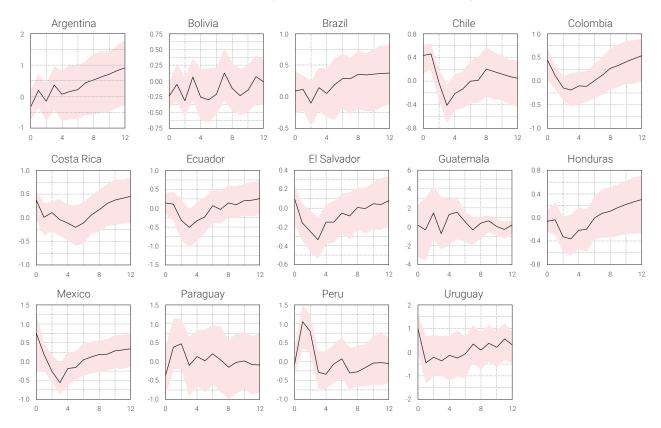


Figure 7. Credit Response to a US Real Uncertainty Shock

Note: The figure shows the response of credit in Latin American countries to US real uncertainty. The shadowed area corresponds to 95% confidence intervals constructed by bootstrapping.

Peru is the only country in which the response to a US real uncertainty shock is positive (remains during only one quarter), while Chile is a special case in which the response is initially positive, but in the third quarter, the response turns negative. It is worth mentioning that credit in Chile also exhibits a positive and immediate response to a US financial uncertainty shock.

The responses of credit to US economic policy uncertainty shocks are presented in Figure 8. The number of countries in which the first significant response is negative is even lower, only three out of fourteen, namely, Bolivia, Chile, and Guatemala. Peru also exhibits a short negative response but after a short positive response. In all other countries, there is no significant response. Finally, Figure 9 depicts the response of credit to a US monetary policy uncertainty shock. Eight out of fourteen countries present a negative response sometime after the occurrence of the US uncertainty shock: Argentina, Chile, Colombia, Costa Rica, Guatemala, Honduras, Mexico, and Uruguay. Costa Rica, however, has a positive response before the negative one. Credit in all other countries is nonresponsive to a US monetary policy uncertainty shock.

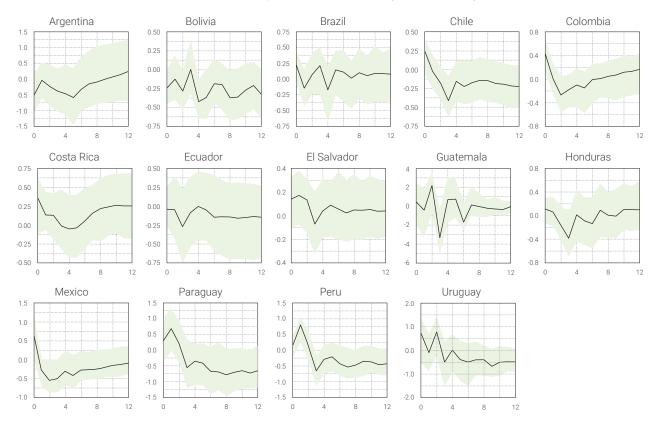


Figure 8. Credit Response to a US Policy Uncertainty Shock

Note: The figure shows the response of credit in Latin American countries to US economic policy uncertainty. The shadowed area corresponds to 95% confidence intervals constructed by bootstrapping.

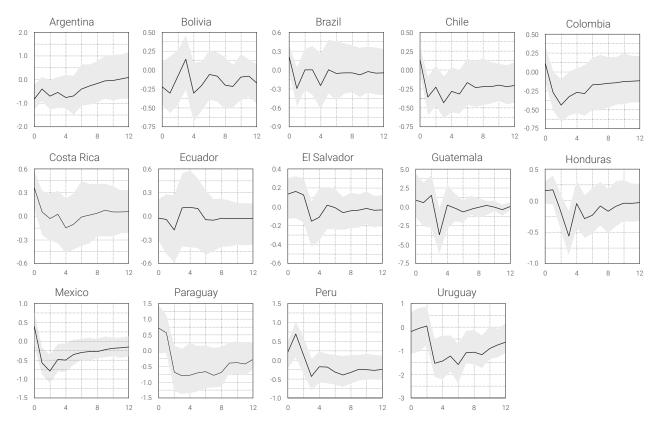


Figure 9. Credit Response to a US Monetary Policy Uncertainty Shock

Note: The figure shows the response of credit in Latin American countries to US monetary policy uncertainty. The shadowed area corresponds to 95% confidence intervals constructed by bootstrapping.

In summary, the responses of credit in LACs countries to US uncertainty shocks are heterogeneous. Negative responses are more common than positive responses, especially to US monetary policy uncertainty shocks, but credit in many countries does not respond to US uncertainty shocks at all.

5.3. Prices

Figures 10 to 13 present the response of prices to the four types of US uncertainty shocks. Here, in all four cases, the black line in each panel represents the median of the identified impulse response functions. The horizontal axis represents time, measured in quarters. The shadowed areas are confidence intervals estimated by bootstrapping (5th and 95th percentiles). The estimation period is 2000g1-2022g2.

The response of prices to a US financial uncertainty shock varies largely in our sample, as seen in Figure 10. In fact, half of the countries (Argentina, Chile, Colombia, Costa Rica, Peru, and Uruguay) respond negatively and immediately. The response of prices in the other three countries (Guatemala, Honduras, and Paraguay) is positive and short-lived. Prices in the other five countries do not respond significantly. There is no particular pattern for classifying these observed responses.

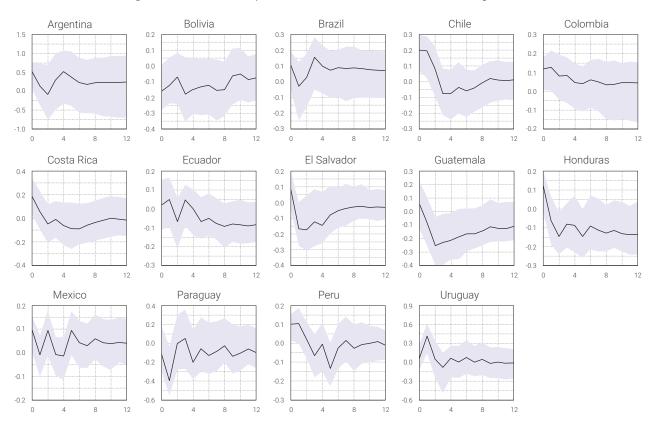


Figure 10. Prices Response to a US Financial Uncertainty Shock

Note: The figure shows the response of inflation in Latin American countries to US financial uncertainty. The shadowed area corresponds to 95% confidence intervals constructed by bootstrapping.

Figure 11 shows the response of prices in LACs countries to a real uncertainty shock originating in the US. Interestingly, there is no country in which prices respond negatively to the shock. For seven countries (Chile, Colombia, Costa Rica, Honduras, Mexico, Paraguay, and Peru), the response is positive, while for the other seven, they are not significant. This implies that a US real uncertainty shock tends to be inflationary in the Latin American region. For most countries that respond to the shock (five out of seven), the reaction is immediate. However, for Colombia and Peru, the response occurs after the sixth quarter and lasts up to the twelfth quarter.

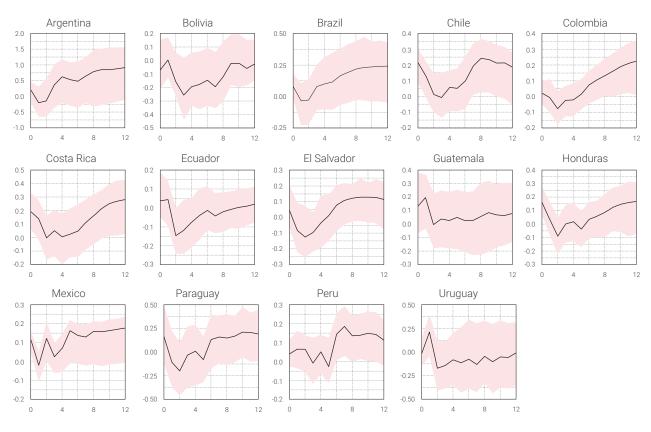


Figure 11. Prices Response to a US Real Uncertainty Shock

Note: The figure shows the response of inflation in Latin American countries to US real uncertainty. The shadowed area corresponds to 95% confidence intervals constructed by bootstrapping.

Prices in most countries (eight out of fourteen) do not react to a US policy uncertainty shock. In Bolivia and Uruguay, prices respond negatively, while in Argentina, Chile, Honduras, and Peru, the response is positive. See Figure 12. A similar behavior is observed for the case of a monetary policy uncertainty shock. Nine out of fourteen countries do not present a significant response. Prices in Argentina and Brazil react positively, while in El Salvador, Mexico, and Uruguay, the response is negative.

Overall, these results indicate two things. First, the response of prices to US uncertainty shocks is highly heterogeneous in Latin America. Second, the strongest transmission channel of US uncertainty shocks to prices in these countries is the real channel. Again, this contrasts with the results obtained by Gomez-Gonzalez *et al.* (2020), who showed that for developed countries, the financial channel predominates.

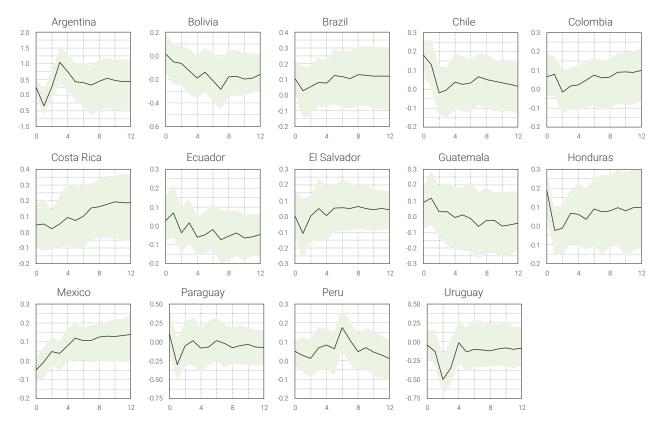


Figure 12. Prices Response to a US Policy Uncertainty Shock

Note: The figure shows the response of inflation in Latin American countries to US economic policy uncertainty. The shadowed area corresponds to 95% confidence intervals constructed by bootstrapping.

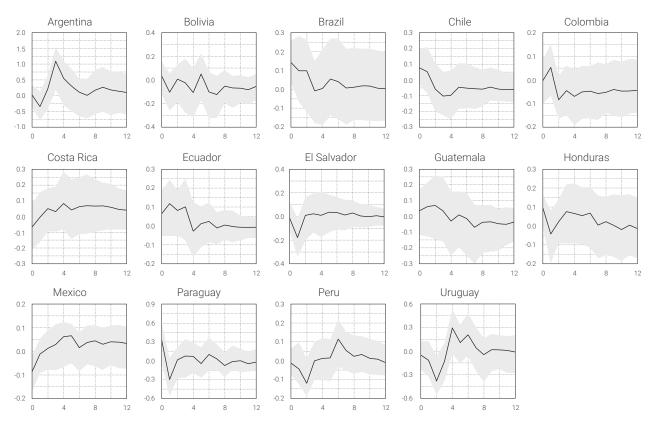


Figure 13. Prices Response to a US Monetary Policy Uncertainty Shock

Note: The figure shows the response of inflation in Latin American countries to US monetary policy uncertainty. The shadowed area corresponds to 95% confidence intervals constructed by bootstrapping.

5.4. Correlation between uncertainty effects in credit, production and prices

A question that naturally emerges relates to the correlation between the reaction of LACs countries to the various types of US uncertainty shocks. Figure 14 graphically responds to that question. It depicts color circles indicating average pairwise correlations. Blue represents a positive correlation, while red represents a negative correlation. The larger the circle and the more intense the color are, the larger the absolute value of the correlation. The correlations of the average responses of GDP to the four types of uncertainty shocks are positive, being higher for the policy and monetary policy uncertainty shocks. The correlations of the average responses of credit to the different types of shocks and credit to these shocks are positive in most cases but less intense. In contrast, the responses of prices to the four shocks are negatively correlated with the responses of the other two variables to US uncertainty shocks. These results indicate that, on average, GDP and credit move in the same direction after a US uncertainty shock, while prices in LACs countries tend to move in the opposite direction.

credit_mpu credit_real prices_fin credit_epu credit_fin dpb-epu gdp_fin 1.0 credit_epu 0.8 credit_real 0.6 gdp_fin gdp_real 0.4 credit_mpu 0.2 gdp_epu 0.0 gdp_mpu -0.2 prices_epu -0.4prices_mpu prices_real -0.6 credit_fin -0.8 prices_fin

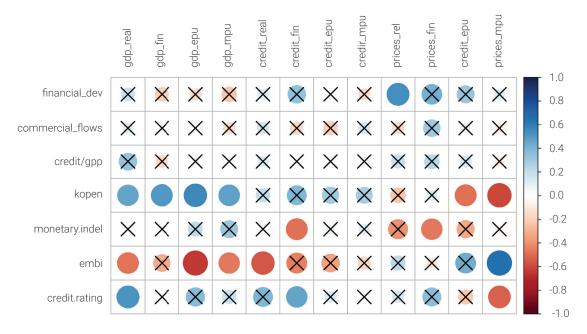
Figure 14. Average Pairwise Correlations between the Responses of Different Variables in LACs to Different Types of US Uncertainty Shocks

Note: The figure shows the pairwise correlation of the four-quarters cumulative effect of US uncertainty proxies (financial, real, economic policy and monetary policy) on credit, GDP and prices. Blue represents a positive correlation while red represents a negative correlation. The larger the circle and the more intense the color are, the larger the absolute value of the correlation.

5.5. Exploratory analysis of the cluster factor for uncertainty effects

In Figure 15, we present an exploratory correlation analysis. The purpose of this analysis is not to establish causality. In fact, even inference is particularly challenging with only 14 data points (one for each country), and we lack a proper causal model to explain the cross-sectional variation in our results. Nonetheless, we aim to set a direction on what variables could underlie the results of our FAVAR models, albeit in a nonconclusive way. Heterogeneity that interests us in this section is in the cross-sectional dimension, unlike our main results in which relevant variation occurred over time.

Figure 15. Average pairwise correlations between the responses of different variables in LACs to different types of US uncertainty shocks and seven possible explanatory variables



Note: The figure shows the pairwise correlation of the four-quarters cumulated effect of US uncertainty proxies (financial, real, economic policy and monetary policy) on credit, GDP and prices with the average value during the sample period of the following variables at an annual frequency: financial development indicator, commercial flows between the US and each country, credit to GDP ratio, financial openness indicator, monetary policy independence indicator, EMBI spread, credit rating. Blue represents a positive correlation, while red represents a negative correlation. The larger the circle and the more intense the color are, the larger the absolute value of the correlation. Correlations that are non-statistically significant at 90% confidence levels are marked with an X.

There are numerous variables that could potentially explain our results. We focus here on the usual suspects from the literature on international financial contagion and market spillovers. In particular, we have explored the following variables: i) the Financial Development Index from the International Monetary Fund, ii) commercial flows between the US and each country, constructed by the ratio of the sum of imports plus exports to US to the total imports plus exports, iii) the ratio of outstanding credit to GDP, iv) financial openness (kopen) and v) monetary policy independence, both of them developed by Chinn and Ito (2006, 2022). The Chinn and Ito index is constructed as the first principal component of a set of variables related to regulations on current or capital account transactions, multiple exchange rates, and surrendering export requirements. vi) the EMBI spread (from JP Morgan), and vii) the country's credit rating (from Standard & Poors).

In most cases, annual data from 2000 to 2021 were collected, except for the financial development indicator, monetary independence, financial openness, and EMBI, for which we lack information for 2021. In all cases, we

took the average in time before estimating the pairwise correlation with the accumulated effects of uncertainty on a one-year horizon in credit, output, and prices. The results are presented in Figure 15.

Most variables fail to capture the cross-sectional variation in the effects that we reported above. Indeed, only the financial openness indicator of Chinn and Ito (2006) shows a significant and positive correlation with the cumulative effect of the four proxies of uncertainty on GDP (as seen in Figures 2 to 5). This means that the less open the country is to global flows, the greater the effects of US uncertainty on output. Openness is also negatively correlated with the effects on prices of the key-word counting measures (EPU and EMU). This means that less open economies also tend to be prone to inflationary pressures of uncertainty, as documented above. Bearing in mind that all economies in our dataset are highly dependent on the US, a lower openness indicator implies that it is also more difficult for such economies to diversify US uncertainty shocks, for instance, by attracting financial flows or investment from third-party countries.

The EMBI tends to be negatively associated with the effects of uncertainty on output, especially with the effects of economic policy uncertainty. This means that the larger the EMBI spread is, the greater the negative effect of uncertainty shocks. In other words, perceived market risk might be a key ingredient in understanding uncertainty propagation, as more fragile countries are also those that face greater output contractions when large uncertainty shocks are observed in the US economy. The same narrative applies to credit ratings, but the sign of the relationship is naturally inverted, as higher ratings are associated with less perceived risk.

6. Conclusions

Recent literature has shown that US uncertainty shocks can affect real and financial variables both in the US and abroad. However, many questions remain open. How do different types of uncertainty shocks affect these variables? What are the main transmission channels? Does the impact of different shocks and their intensity depend on the types of countries that are being studied? In this paper, we contribute to the literature by investigating the effect of four different types of US uncertainty shocks (financial, real, policy, and monetary policy) on a set of fourteen Latin American countries.

We use a FAVAR model in which, for identification purposes, we make use of the theoretical order of contemporaneous exogeneity that our setting allows to study the effect of US uncertainty shocks on credit, output, and prices in LACs. Latin America is one of the most indebted regions in the world and, therefore, particularly sensitive to current uncertainty regarding the monetary policy of the Fed, as well as to other types of uncertainty shocks originating in the US. Additionally, arguably the region has been the most crisis-prone region in the world in the face of international shocks over the past decades, as illustrated by the balance-of-payment crisis in the

1980s and several banking crises in the 1990s. A perverse combination of a weak institutional environment, poorly developed financial markets, and high public debt burdens are at the core of the explanation of why relatively mild shocks arising in the US can have such a strong impact on LACs.

Our results indicate that responses of GDP, credit, and prices in LACs to US uncertainty shocks are highly heterogeneous, depending on the country and the specific type of shock. Responses are not easily clustered according to country characteristics (although financial openness and sovereign risk indicators such as EMBI spreads and a country's credit ratings are significantly correlated with the documented effects of uncertainty in output and prices).

Output responds more strongly to US uncertainty shocks than credit in LACs. In fact, output in the majority of countries responds negatively and significantly, while the response of credit is negative for only a small number of countries. Additionally, the duration of the response of credit tends to be shorter compared to the duration of the response of output. This fact implies that the transmission of US uncertainty shocks to Latin America seems to be explained more by trade and investment channels than by financial channels. This result contrasts with those of the previous literature, which shows that credit and stock markets are important transmission channels of US uncertainty shocks to real variables in developed economies. This possibly responds to the fact that financial markets in emerging market countries are not well developed and their degree of integration with US financial markets is relatively low. Prices in Latin America respond mainly to US real uncertainty prices, as well.

References

- Abel, AB, Eberly, JC. (1996). Optimal investment with costly reversibility, The Review of Economic Studies 63, 581-593.
- Akerlof, GA, Shiller RJ. (2009.) *Animal Spirits: How Human Psychology Drives the Economy and Why It Matters for Global Capitalism*. Princeton, NJ: Princeton University Press.
- Bachmann, R, Bayer, C. (2013). 'Wait-and-See' business cycles? Journal of Monetary Economics 60, 704-719.
- Bai J., Wang, P. (2015). Identification and Bayesian estimation of dynamic factor models, *Journal of Business and Economic Statistics* 33, 221-240.
- Bai, J., Ng, S. (2007). Determining the number of primitive shocks in factor models, *Journal of Business and Economic Statistics* 25, 52-60.
- Baker, S., Bloom, N, Davis, S. (2016). Measuring economic policy uncertainty, Quarterly Journal of Economics 131, 1593-1636.
- Belke, A., Osowski, T. (2019). International effects of Euro area versus US policy uncertainty: A FAVAR approach, *Economic inquiry* 57 453-481.
- Berardi, M. (2022). Uncertainty and sentiments in asset prices, Journal of Economic Behavior and Organization 202, 498-516.
- Berger D., Dew-Becker, I, Giglio, S. (2020). Uncertainty shocks as second-moment news shocks, *The Review of Economic Studies* 87, 40-76.
- Bernanke, B. (1983). Irreversibility, uncertainty and cyclical investment, Quarterly Journal of Economics 98, 85-106.
- Bertola, G., Caballero, R. (1994). Irreversibility and aggregate investment, The Review of Economic Studies 61, 223-246.
- Bhattarai, S., Chatterjee, A., Park, WY (2020). Global spillover effects of US uncertainty, *Journal of Monetary Economics* 114, 71-89.
- Bloom, N. (2009). The impact of uncertainty shocks, Econometrica 77, 623-685.
- Bloom, N., Bond, S., Van Reenen. J. (2007). Uncertainty and investment dynamics, The Review of Economic Studies 74, 391-415.
- Bloom, N., Floetotto, M., Jaimovich, N., Saporta-Eksen, I., Terry, S.J. (2018). Really uncertain business cycles, *Econometrica* 86, 1031-1065.
- Bonciani, D., Van Roye, B. (2016). Uncertainty shocks, banking frictions and economic activity, *Journal of Economic Dynamics and Control* 73, 200-219.
- Bordo, M.D., Duca, J.V., and Koch, C. (2016). Economic policy uncertainty and the credit channel: Aggregate and bank level US evidence over several decades, *Journal of Financial Stability* 26, 90-106.

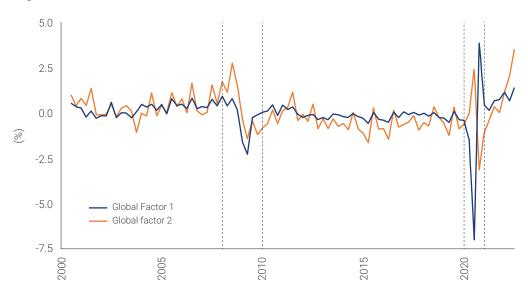
- Brandolini, D., Marzetti S., and Scazzieri, R. (2011). *Fundamental Uncertainty: Rationality and Plausible Reasoning*. London: Palgrave Macmillan.
- Caballero, R.J., Pindyck, R.S. (1996). Uncertainty, investment, and industry evolution, International Economic Review 37,641-662.
- Caldara, D., Iacoviello, M. (2022). Measuring Geopolitical Risk, American Economic Review 112, 1194-1225.
- Canova, F. (2005). The Transmission of US Shocks to Latin America, Journal of Applied Econometrics 20, 229-251.
- Carriero, A., Clark, T.E., Marcellino, M. (2020). Assessing international commonality in macroeconomic uncertainty and its effects, *Journal of Applied Econometrics* 35, 273-293.
- Cesa-Bianchi, A., Pesaran, M.H., Rebucci, A. (2020). Uncertainty and economic activity: A multicountry perspective, *The Review of Financial Studies* 33, 3393-3445.
- Chinn, M., Ito, H. (2006). What Matters for Financial Development? Capital Controls, Institutions, and Interactions, *Journal of Development Economics* 81, 163-192.
- Chinn, M., Ito, H. (2022). Notes on the Chinn-Ito financial openness index 2020 update. Unpublished manuscript available at https://web.pdx.edu/~ito/Readme_kaopen2020.pdf
- Chortareas, G., Noikokyris, E. (2021). Investment, firm-specific uncertainty, and financial flexibility, *Journal of Economic Behavior and Organization* 192, 25-35.
- Chuliá, H., Guillén, M., Uribe, J.M. (2017). Measuring uncertainty in the stock market, *International Review of Economics* and *Finance* 48, 18-33
- Cuaresma, J.C., Huber, F., and Onorante, L. (2020). Fragility and the effect of international uncertainty shocks, *Journal of International Money and Finance* 108, 102151.
- Davidson, P. (1991). Is probability theory relevant for uncertainty? A post Keynesian perspective, *Journal of Economic Perspectives* 5, 129-143.
- Gamba-Santamaria, S., Gomez-Gonzalez, J.E., Hurtado-Guarin, J., Melo-Velandia, L.F. (2017). Stock market volatility spillovers: Evidence for Latin America, *Finance Research Letters* 20, 207-216.
- Garcia-Herrero, A. (2021). Why are Latin American crises deeper than those in emerging Asia, including that of covid-19? ADBI Working Paper Series 1221.
- Gomez-Gonzalez, J.E., Hirs-Garzon, J., Uribe, J.M. (2020). Global effects of US uncertainty: real and financial shocks on real and financial markets, Institut de Recerca en Economia Aplicada Regional i Publica WP # 2020/15, Working papers series of the University of Barcelona.
- Husted, L., Rogers, J., Sun, B. (2020). Monetary policy uncertainty, Journal of Monetary Economics 115, 20-36.
- Istiak, K., and Serletis, A. (2020). Risk, uncertainty, and Leverage, Economic Modelling 91, 257-273.

- Josse, J., Husson, F. (2016). missMDA A Package for Handling Missing Values in Multivariate Data Analysis, *Journal of Statistical Software* 70, 1-31.
- Jurado, K., Ludvigson, S.C., Nq, S. (2015). Measuring uncertainty, American Economic Review 1,1177-1216.
- Kilian, L., Plante, M., Richter (2022). DP17698 Macroeconomic Responses to Uncertainty Shocks: The Perils of Recursive Orderings, CEPR Press Discussion Paper No. 17698. https://cepr.org/publications/dp17698
- Leahy, J., Whited, TM (1996). The effect of uncertainty on investment: some stylized facts, *Journal of Money, Credit and Banking* 28, 64-83.
- Ludvigson, S., Ma, S., Ng, S. (2021). Uncertainty and business cycles: exogenous impulse or endogenous response? *American Economic Journal: Macroeconomics* 13, 369-410.
- Lütkepohl, H. (2006). New Introduction to Multiple Time Series Analysis, Springer.
- Mehrotra, N., and Sergeyev, D. (2021). Financial shocks, firm credit and the Great Recession, *Journal of Monetary Economics* 117, 296-315
- Monnet, E., Puy, D. (2021). One Ring to Rule Them All? New Evidence on World Cycles (March 2021). CEPR Discussion Paper No. DP15958, Available at SSRN: https://ssrn.com/abstract=3816834
- Mumtaz, H., and Theodoridis, K. (2017). Common and country specific economic uncertainty, *Journal of International Economics* 105, 205-216.
- Panagiotidis, T., Printzis, P. (2021). Investment and uncertainty: Are large firms different from small ones? *Journal of Economic Behavior and Organization* 184, 302-317.
- Rey, H. (2018). Dilemma not Trilemma: The global financial cycle and monetary policy independence, NBER working papers 21162, http://www.nber.org/papers/w21162
- Rivolta, G., Trecroci, C. (2020). Measuring the Effects of U.S. Uncertainty and Monetary Conditions on EMEs' Macroeconomic Dynamics, Available at http://dx.doi.org/10.2139/ssrn.3572535
- Segal G., Shaliastovich, I., Yaron, A. (2015). Good and bad uncertainty: Macroeconomic and financial market implications, *Journal of Financial Economics* 117, 369-397.
- Sent, E.M. (2004). Behavioral economics: How psychology made its (limited) way back into economics, *History of Political Economy* 36, 735–760.
- Sims, C.A. (1980). Macroeconomics and reality, Econometrica 48, 1-48.
- Uribe, J.M., Chuliá, H. (2023). Expected, unexpected, good and bad aggregate uncertainty, *Studies in Nonlinear Dynamics & Econometrics*, forthcoming https://doi.org/10.1515/snde-2020-0127
- Wisniewski, T.P., and Lambe, B. (2013). The role of media in the credit crunch: The case of the banking sector, *Journal of Economic Behavior and Organization* 85, 163-175.

- Bachmann, R., Bayer, C. (2013). 'Wait-and-See' business cycles? Journal of Monetary Economics 60, 704-719.
- Nakamura, E., Steinsson, J. (2018). Identification in macroeconomics, The Journal of Economics Perspectives 32, 59-86.
- Stokey, N. (2008). The Economics of Inaction: Stochastic Control Models with Fixed Costs. Princeton, NJ: Princeton University Press.
- Bordo, M.D., Duca, J.V., and Koch, C. (2016). Economic policy uncertainty and the credit channel: Aggregate and bank level US evidence over several decades, *Journal of Financial Stability* 26, 90-106.
- Berger D., Dew-Becker, I., and Giglio S. (2020). Uncertainty shocks as second-moment news shocks, *The Review of Economic Studies* 87, 40-76.
- Caldara, D., Fuentes-Albero, C., Gilchrist, S., Zakrajšek, E. (2016). The macroeconomic impact of financial and uncertainty shocks, *European Economic Review* 88, 185-207.
- Carriero, A., Clark, T.E., Marcellino, M. (2020). Assessing international commonality in macroeconomic uncertainty and its effects, *Journal of Applied Econometrics* 35, 273-293.

Appendix

Figure A1. Global Factors



Note: The figure shows the two global factors estimated using 150 series, for 50 countries of credit, GDP and prices. The dotted vertical lines show the global financial crisis and the Covid19 crisis.

