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Measuring Uncertainty and its effects in a Small Open Economy

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Measuring Uncertainty and its effects in a Small Open Economy

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Abstract

In the aftermath of the 2008 Global Financial Crisis (GFC), scholars and policymakers turned their attention to the role of uncertainty in amplifying the effects of economic or financial shocks on economic activity. A growing literature has focused on addressing this question. Most works find that uncertainty provides an additional transmission mechanism for recessionary shocks, which amplifies their negative effects on the economy. Nonetheless, most of these studies focus on developed economies. It is important to study the effects of uncertainty in the context of small open economies as, unlike developed countries, they are subject to uncertainty from both external and domestic sources. Along these lines, this paper seeks to assess the effects of uncertainty on economic performance in a small open economy and establish the relative importance of external and domestic uncertainty. By using an extended methodology to estimate, simultaneously, a conditional mean model and a stochastic volatility factor model, it is possible to estimate reliable uncertainty measures and describe their distinct dynamics. The impulse-response analysis shows that rising uncertainty produces negative effects on economic activity in a small open economy, and the largest effects happen when external uncertainty climbs. However, we found an intriguing effect: when uncertainty rises, business loans tend to increase immediately after the shock, but return rapidly to their equilibrium level.

Keywords: Uncertainty; Stochastic volatility; Dynamic Factor models.
JEL: E44, C11, C13, C32, C55

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1 Introduction

In economics, uncertainty is understood as the inability of economic agents (households, firms, and policymakers) to foresee relevant economic developments. Therefore, a decision-maker must make assumptions to predict the most reasonable future path of the outcomes of interest given the available information. Thus, the more difficult it is to predict outcomes, the more likely it is to make erroneous decisions. In consequence, changes in the uncertainty level may affect policymakers' decisions. In general, economic agents are continuously concerned about the economic outlook for making decisions.

Uncertainty (which is exacerbated by shocks such as terrorist attacks, political crises, or the outbreak of a pandemic event) affects the variance size of economic variables. For instance, following the 9/11 terrorist attacks, there was a significant surge in stock market volatility (a standard proxy for financial and macroeconomic uncertainty). Moreover, household and business expectations deteriorated abruptly, leading to a considerable drop in investment and consumption. Therefore, it is relevant to quantify to what extent changes in uncertainty affect economic activity.

In the aftermath of the 2008 Global Financial Crisis (GFC), most scholars and policymakers turned their attention to uncertainty as an additional, relevant transmission mechanism for explaining the depth and persistence of the adverse effects of the financial turmoil. Bloom (2009) uses a structural model for quantifying the impact of a climb in uncertainty, finding that an uncertainty shock (defined as a significant increase in the variance of the productivity shock) worsens business conditions and induces firms to reduce their labor demand and equilibrium production; i.e., higher uncertainty makes firms pause their investment and hiring decisions in the short term; but results in overshooting of output and employment in the medium term.

Mumtaz and Zanetti (2013) study the impact of monetary uncertainty shocks on real output and other outcomes. The study enriches the standard structural vector auto-regression framework by allowing time-varying stochastic volatility of structural shocks, as well as a dynamic interaction between stochastic volatility and the level of observable variables. Their findings show that output growth, interest rates, and inflation fall in response to an increase in the volatility of a monetary policy shock. For investigating the transmission mechanisms, the authors construct a DSGE model and solve it by third-order approximation. The higher uncertainty of a monetary policy shock leads to higher spreads and inflation dispersion, in turn reducing inflation expectations. In this context, bond investors demand smaller compensation to keep bonds in their portfolio, leading to a fall in nominal interest rates. The Taylor rule and the Phillips curve indicate that inflation and output growth decrease as well.

Christiano et al. (2014) analyze the effects of uncertainty within a DSGE model that allows for financial frictions (Townsend (1979); Bernanke et al. (1999)). They define uncertainty as the time-varying, idiosyncratic volatility of a structural shock. They find that risk shocks (a surge in uncertainty) provoke counter-cyclical credit spreads and pro-cyclical investment, consumption, employment, inflation, and credit. That is, a rise in uncertainty increases credit premiums, which contracts credit to businesses. The latter reduce their investment in physical capital, leading to a decrease in output, consumption, and employment. This decline in economic activity ultimately provokes a fall in inflation. Along the same lines, Arellano et al. (2012) study the effects of higher volatility of firm-level idiosyncratic shocks. Their model considers imperfect financial markets and fixed entrance costs. In their analysis, labor demand balances off between an increase in expected returns and potential losses from default. Thus, when the dispersion of idiosyncratic shocks rises, the probability of default climbs as well as the labor wedge. This leads firms to become more cautious in equilibrium, which provokes a reduction in labor demand; and causes, on aggregate, a reduction in employment and production.

Baker and Bloom (2013) approach the causal relationship between uncertainty and economic activity from an empirical point of view. They employ natural disasters, terrorist attacks, and political crises as instruments for stock market returns and volatility. Their identification assumption is based on the argument that some shocks (natural disasters) affect primarily stock market returns, while other shocks (political crises) mainly affect stock market volatility. The estimation results point out that a one-standard-deviation shock on stock market levels and volatility has a negative effect of around 1.61% and 1.64% on GDP growth a quarter after a natural disaster, respectively. A year after the shock, these effects on GDP growth mount to around 2.20% and 7.11%, respectively.

Distinguishing financial from macroeconomic uncertainty is a critical empirical challenge, as both are significantly correlated with different observable variables (credit spreads and stock market volatility, among others). Caldara et al. (2016) add a penalty function to the standard SVAR model to discriminate between both uncertainty shocks. Their results suggest three important conclusions: first, financial shocks provoke significant adverse effects on economic activity; i.e., they are an important source of economic fluctuations. Second, uncertainty shocks that are not related to financial asset prices are an important source of macroeconomic disturbances. Finally, uncertainty shocks are especially relevant and have stronger adverse effects on economic activity if the economy is struggling with tight financial conditions.

Most empirical studies employ some measure of uncertainty (financial or macroeconomic) but, as we mentioned above, as uncertainty is an unobservable variable, it must be approximated or estimated using observable information. Baker et al. (2016) develop an index of economic policy uncertainty (EPU) constructed from media news; i.e., analyzing the frequency of keywords such as *economic or economy*, *uncertain or uncertainty*, *Congress*, *deficit*, and *Federal Reserve*, among others, in the top 10 U.S. newspapers. The raw frequency for each newspaper is standardized by the number of articles in the same newspaper during a given month, thereby obtaining a series for each newspaper. Finally, each series is expressed in standard deviations from 1985 to 2009. The results show that the EPU index spikes for critical events such as the Gulf War, Black Monday, the 9/11 attacks, the Lehman bankruptcy, and the euro crisis, among others. To assess potential issues regarding the accuracy and reliability of the index, we compare it with other proxies of economic uncertainty, such as the implied volatility of stock markets. We find a strong positive relationship with this proxy, as well as with uncertainty measures constructed from the Federal Reserve's Beige Book. Moreover, the findings suggest that firms with high exposure to government procurement experience greater stock price volatility when the EPU index is high; and that firms reduce their investment and labor demand when the EPU index rises.

Jurado et al. (2015) provide a measure of macroeconomic uncertainty using a large number of variables. They aim to obtain measures of financial and macroeconomic uncertainty related to economic activity (thereby departing from other measures, which may not be related to economic fundamentals, such as the implied volatility of stock market indices). Their premise is that what matters is not whether a variable is more volatile or dispersed, but whether the economy has become less predictable. Under this approach, the uncertainty level is the weighted aggregate of the conditional volatility of forecast errors; i.e., uncertainty is not related to single-variable volatility but is rather a measure of common variation across different observable macroeconomic and financial variables. The authors construct two indices, one based on hundreds of macroeconomic and financial aggregates, intended to capture *common macroeco-*

nomic uncertainty; and a second one, based on 155 firm-level variables, that captures *common firm-level uncertainty*. They employ a medium-size SVAR model identified with recursive restrictions (with uncertainty as the most endogenous variable) to show the reliability of their measures, finding that uncertainty accounts for 29% of the forecast error variance in industrial production.

Most empirical contributions to the literature rely on a two-stage approach, consisting of estimating the uncertainty index and then using it as input in a macro-econometric model for assessing the impact on observable outcomes. This procedure makes it difficult to draw inferences from the second-stage estimations, as it must consider the estimation error in the first stage. Creal and Wu (2017) seek to internalize the estimation of uncertainty into the estimation of the model. They use a multivariate VAR model with stochastic volatility modeled as a GARCH process, which allows stochastic volatility to affect endogenous observable outcomes. The estimated impulse-response functions suggest that monetary policy and term premium uncertainty increase unemployment, which is consistent with the findings of Mumtaz and Zanetti (2013). However, the median response of inflation is close to zero and non-significant. Nonetheless, if the responses are computed conditional to the state (which is possible under their approach), they differ from the unconditional responses. Under the GFC, the response of unemployment to monetary policy and term premium uncertainty is still positive, but much stronger, while the inflation response is significantly different.

Carriero et al. (2018) and Creal and Wu (2017) point out the issues around the variability of uncertainty estimations in the two-stage procedure. They also claim that most first-stage uncertainty estimations are based on a large cross-section database, while the second-stage estimations considered only a few observable outcomes, thereby introducing an omitted-variable bias. Additionally, they claim that in some cases the two-stage procedure is somewhat contradictory, as first-step estimations are based on the assumption that variables have time-varying volatility, while the second step denies it. In order to overcome these issues, they proposed an SVAR model enriched with a dynamic common factors model for the time-varying volatility, which is intended as the measure of uncertainty. Additionally, as in GARCH-M models, they allow the unobserved common factors to affect the conditional mean and add the possibility of feedback from observable variables to common factor dynamics. Their results show that the number of common factors considered captures a significant proportion of the stochastic volatility of the observable variables, although the variability of the idiosyncratic component is not negligible. Under this single-step estimation, the variability of uncertainty estimates is easily quantifiable. Regarding the effects of common factors, the impulse-response analysis shows that the macroeconomic uncertainty common factor has an important effect on macroeconomic variables, but a limited one on financial outcomes. On the contrary, financial uncertainty elicits a significant response from financial variables, in turn generating a response from macroeconomic outcomes.

Regardless of the valuable contributions so far, there is still a gap in the literature, as most studies in this field focus on developed economies. It is important to address the case of emerging, small open economies, which are exposed to multiple sources of uncertainty. Of particular relevance is the uncertainty originating from the external sector, as most emerging economies are highly connected to developed economies via world trade; and, importantly, their financial markets are deeply linked to major stock markets. Thus, it is important to distinguish between domestic and external sources of uncertainty, as their effects, although similar in direction, may differ greatly in magnitude.

Therefore, this paper aims to assess empirically the effects of domestic and external uncertainty on macroeconomic and financial variables in Peru. Our econometric approach is based on adapting the work by Carriero et al. (2018) to the features of an emerging economy. The advantage of employing the approach suggested by Carriero et al. is that it avoids a two-step estimation, thereby making inference more accurate. The main difference between our framework and their original work is that we introduce an exogenous block to assess the type of dependence prevailing in a small open economy. Besides, unlike Carriero et al., we allow for a non-diagonal common factor structure in time-varying volatility.

Our identified unobserved measures of uncertainty capture important events at the international and domestic levels. In particular, our measure of external uncertainty rises during the GFC and the European debt crisis. On the other hand, the domestic financial and macroeconomic uncertainty measures are more related to internal events, such as political crises. Regarding the effects of shocks (captured by our uncertainty measures) on the observable variables, the largest negative impacts occur when external uncertainty rises, which is consistent with the fact that Peru is dependent on international financial and commodity markets. A surprising effect, present in all uncertainty measures, is that business credit rises significantly in response to an external or domestic financial uncertainty shock. This likely reflects a new stylized fact regarding firm behavior; i.e., in a context of increased uncertainty, firms enhance their working capital contemporaneously as a way to prevent liquidity problems.

The remainder of the article is structured as follows: Section (2) details the econometric model, focusing on explaining the block exogeneity restrictions; Section (3) describes the estimation procedure, which is based on Carriero et al. (2018); Section (4) presents the data and the main descriptive statistics; Section (5) summarizes the main results; and Section (6) concludes.

2 Econometric Model

Let $\boldsymbol{y}_t$ be a vector-valued, stationary, ergodic process of dimension n. Additionally, $\boldsymbol{y}_t$ is divided along two dimensions: by origin (i.e., external or domestic) and by type (i.e., macroeconomic or financial). In principle, we have four possible combinations; but, as we combine external macroeconomic and financial variables into a single category, we obtain three sources of uncertainty. Hence, n_E denotes the variables of external origin; and n_{mD} and n_{fD} denote the macroeconomic and financial variables of domestic origin, respectively. Thus, $n = n_E + n_{fD} + n_{mD}$. The ordering selected is the following: $\boldsymbol{y}_t = \begin{bmatrix} \boldsymbol{y}'_{t,E} & \boldsymbol{y}'_{t,fD} & \boldsymbol{y}'_{t,mD} \end{bmatrix}'$.

The extended structural VAR model is the following:

$$\boldsymbol{y}_t = \sum_{j=1}^{p} \boldsymbol{\Pi}_j \boldsymbol{y}_{t-j} + \sum_{j=0}^{p_\xi} \boldsymbol{\Pi}_j^\xi \boldsymbol{\xi}_{t-j} + \boldsymbol{\nu}_t \tag{1}$$

where p is the number of lags of $\boldsymbol{y}_t$ and p_ξ the number of lags of the uncertainty measures $\boldsymbol{\xi}_t$, which is a 3-dimensional vector. Additionally, $\boldsymbol{\nu}_t$ is the vector of heteroskedastic, structural shocks. Moreover, it is imposed that $\det\left(\sum_{j=0}^{p} \boldsymbol{\Pi}_j z^j\right) \neq 0$ for all $|z| \leq 1$. It is important to note the difference between this framework and that proposed by Creal and Wu (2017), which allows volatility to affect observable variables directly. In contrast, our model only allows common factors of volatilities ($\boldsymbol{\xi}_t$) to affect the conditional mean.

The residuals $\boldsymbol{\nu}_t$ follow a similar structure to the one proposed by Primiceri (2005) and Cogley and Sargent (2005). Additionally, $\boldsymbol{\nu}_t = \boldsymbol{A}^{-1} \boldsymbol{\Lambda}_t^{1/2} \boldsymbol{\varepsilon}_t$, where $\boldsymbol{A}$ is a time-invariant, full rank matrix of dimension n; and $\boldsymbol{\Lambda}_t = \operatorname{diag}\begin{pmatrix} \lambda_{1,t} & \dots & \lambda_{n,t} \end{pmatrix}'$ is the matrix of heteroskedastic conditional volatilities. Moreover, $\boldsymbol{\varepsilon}_t$ is an n-dimensional white noise, Gaussian process with $\mathbb{E}\boldsymbol{\varepsilon}_t = \boldsymbol{0}$ and $\mathbb{E}\boldsymbol{\varepsilon}_t \boldsymbol{\varepsilon}'_t = \boldsymbol{I}_n$.

The dynamic factor model for time-varying volatilities is the following:

$$\ln \lambda_{j,t} = \begin{cases} \beta_j^{E,E} \ln \xi_{E,t} + \ln h_{j,t}, & j = 1, \dots, n_E \\ \beta_j^{fD,fD} \ln \xi_{fD,t} + \beta_j^{fD,E} \ln \xi_{E,t} + \ln h_{j,t}, & j = n_E + 1, \dots, n_E + n_{fD} + 1 \\ \beta_j^{mD,mD} \ln \xi_{mD,t} + \beta_j^{mD,fD} \ln \xi_{fD,t} + \beta_j^{mD,E} \ln \xi_{E,t} + \ln h_{j,t}, & j = n_E + n_{fD} + 1, \dots, n \end{cases} \tag{2}$$

Equation (2) differs from that stated by Carriero et al. (2018) in that: (i) the time-varying volatility of external macroeconomic and financial variables are explained by a common factor $\ln \xi_{E,t}$, which captures the uncertainty of the external source; (ii) the volatilities of domestic financial variables is explained by the external uncertainty measure $\ln \xi_{E,t}$, but they also share a common factor of domestic origin $\ln \xi_{fD,t}$; and (iii) the volatilities of domestic macroeconomic variables are explained by both external and domestic uncertainty factors, and they also share a common part $\ln \xi_{mD,t}$. If $\beta_j^{fD,E} = \beta_j^{mD,E} = \beta_j^{mD,fD} = 0$ we obtain a similar structure to the one proposed by Carriero et al. (2018).

In addition, $\ln h_{j,t}$ denotes the idiosyncratic component of the stochastic volatilities. This idiosyncratic component evolves according to:

$$\ln h_{j,t} = \gamma_{j,0} + \gamma_{j,1} \ln h_{j,t-1} + e_{j,t}, \quad j = 1, \dots, n \tag{3}$$

Using vector notation, equation (3) is equivalent to

$$\ln \boldsymbol{h}_t = \boldsymbol{\gamma}_0 + \boldsymbol{\Gamma}_1 \ln \boldsymbol{h}_{t-1} + \boldsymbol{e}_t$$

where $\boldsymbol{e}_t = \begin{pmatrix} e_{1,t} & \dots & e_{n,t} \end{pmatrix}'$ is Gaussian distributed with $\mathbb{E}\boldsymbol{e}_t = \mathbf{0}$ and $\mathbb{E}\boldsymbol{e}_t\boldsymbol{e}_t' = \boldsymbol{\Phi}_e = \text{diag}\Big(\phi_1, \dots, \phi_n\Big)$. This implies that the components in $\boldsymbol{e}_t$ are mutually independent. $\boldsymbol{\Gamma}_1 = \text{diag}(\gamma_{1,1}, \dots, \gamma_{n,1})$. Moreover, we assume that $\boldsymbol{e}_t$ and $\boldsymbol{\varepsilon}_t$ are independent.

Common factors evolve according to:

$$\begin{bmatrix} \ln \xi_{E,t} \\ \ln \xi_{fD,t} \\ \ln \xi_{mD,t} \end{bmatrix} = \boldsymbol{D}(L) \begin{bmatrix} \ln \xi_{E,t-1} \\ \ln \xi_{fD,t-1} \\ \ln \xi_{mD,t-1} \end{bmatrix} + \begin{bmatrix} \boldsymbol{\delta}_E' \\ \boldsymbol{\delta}_{fD}' \\ \boldsymbol{\delta}_{mD}' \end{bmatrix} \begin{bmatrix} \boldsymbol{y}_{t,E} \\ \boldsymbol{y}_{t,fD} \\ \boldsymbol{y}_{t,mD} \end{bmatrix} + \begin{bmatrix} \eta_{t,E} \\ \eta_{t,fD} \\ \eta_{t,mD} \end{bmatrix} \tag{4}$$

$\boldsymbol{I}_n - \boldsymbol{D}(L) = \boldsymbol{I}_n - \sum_{j=1}^d \boldsymbol{D}_j L^j$ is a lag polynomial of order d. We assume that $\det(\boldsymbol{I}_n - \boldsymbol{D}(z)) \neq 0$ for all $|z| \leq 1$. In contrast with Carriero et al. (2018), we impose some exclusion restrictions on equation (4).

First, we impose zero restrictions on lag polynomial $\boldsymbol{D}(L)$. In particular $\boldsymbol{D}_j = \begin{bmatrix} d_{11,j} & 0 & 0 \\ d_{21,j} & d_{22,j} & 0 \\ d_{31,j} & d_{32,j} & d_{33,j} \end{bmatrix}$. These restrictions imply that we allow external uncertainty common factor $\ln \xi_{E,t}$ to affect the dynamics of domestic uncertainty factors, but not vice versa. Second, the matrix $\boldsymbol{\delta}$ has the following structure: $\boldsymbol{\delta}' = \begin{bmatrix} \boldsymbol{\delta}'_{E,E} & \mathbf{0}'_{n_{fD}} & \mathbf{0}'_{n_{mD}} \\ \boldsymbol{\delta}'_{fD,E} & \boldsymbol{\delta}'_{fD,fD} & \mathbf{0}'_{n_{mD}} \\ \boldsymbol{\delta}'_{mD,E} & \boldsymbol{\delta}'_{mD,fD} & \boldsymbol{\delta}'_{mD,mD} \end{bmatrix}$. We assume the structure of $\boldsymbol{\eta}_t$ to be Gaussian white noise with $\mathbb{E}\boldsymbol{\eta}_t\boldsymbol{\eta}_t' = \boldsymbol{\Phi}_\eta$, a symmetric, positive definite matrix.

In Carriero et al. (2018), matrix $\boldsymbol{\Phi}_\eta$ is non-diagonal, because it captures potential dependence among uncertainty measures (not accounted for with diagonal loading factors). In our case, since we are introducing non-diagonal loading factors, it is possible to restrict the structure of $\boldsymbol{\Phi}_\eta$.

On the other hand, identification of factor loadings $\beta_{i,j}$ requires the impossibility of orthogonal rotations to factor loadings, which can be achieved by setting $\beta_1^{E,E} = \beta_{1+n_E}^{fD,fD} = \beta_{1+n_E+n_{fD}}^{mD,mD} = 1$ as in Carriero et al. (2018). Additionally, we impose a recursive structure on $\boldsymbol{A}$ by fixing its diagonal elements to 1.

3 Estimation

We use a standard Monte Carlo Markov Chain (MCMC) sampler for estimating the model (equations (1)-(4)). The total number of draws is $30 \cdot 10^3$, from which the first $5 \cdot 10^3$ are discarded; and every fifth draw is selected from the remaining ones. The MCMC sampler operates in two steps. First, it draws the idiosyncratic components using a standard state-space system. To estimate $\ln(\lambda_{j,t})$ we use the re-scaled reduced form residuals $\tilde{\boldsymbol{u}}_t = \boldsymbol{A}\boldsymbol{u}_t$ and a measure of conditional log-volatility given by $\ln(\tilde{u}_{j,t}^2 + \bar{c})$, where $\bar{c}$ has constant values to avoid problems with values close to zero. Thus, given the initial paths for the unobserved measures of uncertainty, the system to be solved is the following:

$$\begin{cases} \ln(\tilde{u}_{j,t}^2 + \bar{c}) - \beta_j^{E,E} \ln \xi_{E,t} = \ln h_{j,t} + \ln \epsilon_{j,t}^2, & j = 1, \ldots, n_E \\ \ln(\tilde{u}_{j,t}^2 + \bar{c}) - \beta_j^{fD,fD} \ln \xi_{fD,t} - \beta_j^{fD,E} \ln \xi_{E,t} = \ln h_{j,t} + \ln \epsilon_{j,t}^2, & j = n_E + 1, \ldots, n_E + n_{fD} + 1 \\ \ln(\tilde{u}_{j,t}^2 + \bar{c}) - \beta_j^{mD,mD} \ln \xi_{mD,t} - \beta_j^{mD,fD} \ln \xi_{fD,t} - \beta_j^{mD,E} \ln \xi_{E,t} = \ln h_{j,t} + \ln \epsilon_{j,t}^2, & j = n_E + n_{fD} + 1, \ldots, n \end{cases}$$

This system is linear but non-Gaussian, even though $\epsilon_{j,t}$ is Gaussian distributed. For approximating a Gaussian system, we follow the procedure suggested by Kim et al. (1998); i.e., introducing the state variable sequence $\{\boldsymbol{s}_t\}$. Finally, in order to draw the factor loadings $\boldsymbol{\beta}$, we use the posterior distribution detailed below.

The second step draws the remaining parameter values and common factors, conditional on the idiosyncratic volatilities and factor loadings from the previous step. The posterior distributions are stated below.

Let $\boldsymbol{a}_j$ denote the j-th row of $\boldsymbol{A}$ with size $j-1$ for $j = 2, \dots, n$. Additionally, $\boldsymbol{\gamma}_j = (\gamma_{j,0}, \gamma_{j,1})'$ is the vector containing the intercept and slope of equation (3); and $\boldsymbol{\gamma} = \begin{pmatrix}\boldsymbol{\gamma}_1' & \dots & \boldsymbol{\gamma}_n'\end{pmatrix}'$. $\boldsymbol{\Delta} = \begin{pmatrix}\boldsymbol{D}'(L) & \boldsymbol{\delta}\end{pmatrix}$ is the matrix of coefficients of transition dynamics in equation (4). $\boldsymbol{\Pi} = \left(\boldsymbol{\Pi}_1, \dots, \boldsymbol{\Pi}_p, \boldsymbol{\Pi}_0^{\xi}, \dots, \boldsymbol{\Pi}_{p_\xi}^{\xi}\right)$ is the matrix of coefficients for the conditional mean of the endogenous observable variables. $\boldsymbol{h}_{1:T}$ and $\boldsymbol{\xi}_{1:T}$ denotes the sequence of time series of state variables (idiosyncratic and uncertainty common factors). $\boldsymbol{s}_{1:T}$ is the time series sequence of the unobserved mixture of states employed for implementing the approach proposed by Kim et al. (1998).

Prior Distributions

Following Carriero et al. (2018); Primiceri (2005), we employ the following prior distributions:

$$
\begin{aligned}
\text{vec}(\boldsymbol{\Pi}) &\sim \mathcal{N}\left(\boldsymbol{\mu}_{\Pi}^0, \boldsymbol{\Omega}_{\Pi}^0\right) \\
\boldsymbol{a}_j &\sim \mathcal{N}\left(\boldsymbol{\mu}_{a,j}^0, \boldsymbol{\Omega}_{a,j}^0\right), \quad j = 2\dots, n \\
\boldsymbol{\beta}_j &\sim \mathcal{N}\left(\boldsymbol{\mu}_{\beta,j}^0, \boldsymbol{\Omega}_{\beta,j}^0\right), \quad j = 2\dots, n \\
\boldsymbol{\gamma}_j &\sim \mathcal{N}\left(\boldsymbol{\mu}_{\gamma,j}^0, \boldsymbol{\Omega}_{\gamma,j}^0\right), \quad j = 1\dots, n \\
\boldsymbol{\delta} &\sim \mathcal{N}\left(\boldsymbol{\mu}_{\delta}^0, \boldsymbol{\Omega}_{\delta}^0\right) \\
\phi_j &\sim IG\left(d_\phi \phi^0, d_\phi\right), \quad j = 1, \dots, n \\
\boldsymbol{\Phi}_\eta &\sim IW\left(d_{\Phi_\eta}\boldsymbol{\Phi}_\eta^0, d_{\Phi_\eta}\right)
\end{aligned}
$$

where $IG(\alpha, \beta)$ denotes an inverse Gamma density function with shape (α) and scale (β) parameters; and $IW(\boldsymbol{\Psi}, d)$ denotes an inverse Wishart density function with scale matrix, $\boldsymbol{\Psi}$, and degrees of freedom d.

Posterior Distributions

Following Carriero et al. (2018), and given the prior distributions, the posterior densities are (technical details follow Cogley and Sargent (2005) work):

$$\begin{aligned}
\text{vec}(\mathbf{\Pi})|\boldsymbol{A},\boldsymbol{\beta},\boldsymbol{\xi}_{1:T},\boldsymbol{h}_{1:T},\boldsymbol{y}_{1:T} &\sim \mathcal{N}\left(\boldsymbol{\mu}^1_{\Pi},\mathbf{\Omega}^1_{\Pi}\right) \\
\boldsymbol{a}_j|\text{vec}(\mathbf{\Pi}),\boldsymbol{\beta},\boldsymbol{\xi}_{1:T},\boldsymbol{h}_{1:T},\boldsymbol{y}_{1:T} &\sim \mathcal{N}\left(\boldsymbol{\mu}^1_{a,j},\mathbf{\Omega}^1_{a,j}\right), \quad j=2,\ldots,n \\
\boldsymbol{\beta}_j|\text{vec}(\mathbf{\Pi}),\boldsymbol{A},\boldsymbol{\gamma},\mathbf{\Phi}_e,\mathbf{\Phi}_\eta,\boldsymbol{\xi}_{1:T},\boldsymbol{h}_{1:T},\boldsymbol{s}_{1:T},\boldsymbol{y}_{1:T} &\sim \mathcal{N}\left(\boldsymbol{\mu}^1_{\beta,j},\mathbf{\Omega}^1_{\beta,j}\right), \quad j=2,\ldots,n \\
\boldsymbol{\gamma}_j|\text{vec}(\mathbf{\Pi}),\boldsymbol{A},\boldsymbol{\beta},\mathbf{\Phi}_e,\mathbf{\Phi}_\eta,\boldsymbol{\xi}_{1:T},\boldsymbol{h}_{1:T},\boldsymbol{y}_{1:T} &\sim \mathcal{N}\left(\boldsymbol{\mu}^1_{\gamma,j},\mathbf{\Omega}^1_{\gamma,j}\right), \quad j=1,\ldots,n \\
\boldsymbol{\delta}|\text{vec}(\mathbf{\Pi}),\boldsymbol{A},\boldsymbol{\beta},\boldsymbol{\gamma},\mathbf{\Phi}_e,\mathbf{\Phi}_\eta,\boldsymbol{\xi}_{1:T},\boldsymbol{h}_{1:T},\boldsymbol{y}_{1:T} &\sim \mathcal{N}\left(\boldsymbol{\mu}^1_{\delta},\mathbf{\Omega}^1_{\delta}\right) \\
\phi_j|\text{vec}(\mathbf{\Pi}),\boldsymbol{A},\boldsymbol{\beta},\boldsymbol{\gamma},\boldsymbol{\xi}_{1:T},\boldsymbol{h}_{1:T},\boldsymbol{y}_{1:T} &\sim IG\left(d_\phi\phi^0+\sum_{t=1}^{T}\nu^2_{j,t},d_\phi+T\right), \quad j=1,\ldots,n \\
\mathbf{\Phi}_\eta|\text{vec}(\mathbf{\Pi}),\boldsymbol{A},\boldsymbol{\beta},\boldsymbol{\gamma},\boldsymbol{\xi}_{1:T},\boldsymbol{h}_{1:T},\boldsymbol{y}_{1:T} &\sim IW\left(d_{\Phi_\eta}\mathbf{\Phi}^0_\eta+\sum_{t=1}^{T}\boldsymbol{\eta}_t\boldsymbol{\eta}'_t,d_{\Phi_\eta}+T\right)
\end{aligned}$$

To draw vec($\mathbf{\Pi}$), we follow the procedure proposed by Carriero et al. (2018); i.e., equation by equation. Notice that m-th equation in the extended SVAR model can be written as:

$$y_{m,t}=\sum_{j=1}^{p}\sum_{d=1}^{n}\pi_{j,d}y_{d,t-j}+\sum_{j=0}^{p_\xi}\sum_{d=1}^{3}\pi^\xi_{j,d}\ln\xi_{d,t-j}+\sum_{j=1}^{m-1}\boldsymbol{a}^{(-1)}_{m,j}r_{j,t}+r_{m,t}$$

where $r_{i,t}=\lambda^{1/2}_{i,t}\varepsilon_{i,t}$ and $\boldsymbol{a}^{(-1)}_{m,j}$ is the (m,j) element of A^{-1}. Since $\boldsymbol{A}$, $\boldsymbol{\beta}$, and the unobserved factors are given, the previous equation is equivalent to:

$$y_{m,t}-\sum_{j=1}^{m-1}\boldsymbol{a}^{(-1)}_{m,j}r_{j,t}=y^\star_{m,t}=\sum_{j=1}^{p}\sum_{d=1}^{n}\pi_{j,d}y_{d,t-j}+\sum_{j=0}^{p_\xi}\sum_{d=1}^{3}\pi^\xi_{j,d}\ln\xi_{d,t-j}+r_{m,t}$$

Collecting the sample from 1 to T,

$$\boldsymbol{y}^\star_m=\boldsymbol{X}\boldsymbol{\pi}_m+\boldsymbol{r}_m$$

where $\boldsymbol{y}^\star_m=\begin{bmatrix}y^\star_{m,1} & y^\star_{m,2} & \cdots & y^\star_{m,T}\end{bmatrix}'$, $\boldsymbol{r}_m=\begin{bmatrix}r_{m,1} & r_{m,2} & \cdots & r_{m,T}\end{bmatrix}'$ and $\boldsymbol{\pi}_m$ is the m-column of $\mathbf{\Pi}$ or the m-th block of vec($\mathbf{\Pi}$).

Therefore, given the triangular structure of $\boldsymbol{A}^{-1}$, we obtain

$$\boldsymbol{\pi}_m|\boldsymbol{\pi}_{1:m-1},\boldsymbol{A},\boldsymbol{\beta},\boldsymbol{\xi}_{1:T},\boldsymbol{h}_{1:T},\boldsymbol{y}_{1:T}\sim\mathcal{N}\left(\boldsymbol{\mu}^1_{\Pi,m},\mathbf{\Omega}^1_{\Pi,m}\right)$$

4 Data

We use data for 31 variables, which can be divided into three groups: (i) external, (ii) domestic financial, and (iii) domestic macroeconomic. The first group includes spreads (price) and quantity measures related to multiple macroeconomic and financial dimensions, such as liquidity measures or real-estate pricing, among others. The second group includes different measures for the evolution of domestic stock and credit markets. Finally, the domestic macroeconomic group includes real variables, as well as information linked to international trade (price and quantity indices). The monthly series cover from January 2007 to September 2009; i.e., a sample size of $T = 177$ observations. Additionally, except for the measures for spreads and the interest rate, the variables have been seasonally adjusted and expressed in logarithms. Moreover, all series showing a persistent behavior (i.e., close to the unit root) were transformed to first differences. The following table shows the variables included in the estimation.

Table (2) shows the main descriptive statistics for the full sample, including the COVID-19 pandemic episode. The average monthly growth rate for non-primary manufacturing is about 0.2%, while its median is about 0.4%. However, this measure shows considerable dispersion: the standard deviation is 7.2% and the inter-quantile range (IQR) is 4.3%. Regarding 3-month expectations, the average is 5.4 points above the neutral value (50), while its standard deviation is twice its mean. Concerning household credit, the average monthly growth rate is 1.06% with a standard deviation of around 0.9%.

Regarding domestic financial measures, it can be noted that business credit growth is 1.13%, similar to household credit growth; but its standard deviation is twice that of household loans, consistent with the fact that business credit is related to investment, while household loans are related to consumption. On the other hand, business and household delinquency rates have opposite behaviors, at least on average. The household delinquency portfolio has an average growth rate of around 1.6%, while the delinquency of business loans grows at 0.4%, on average. At the same time, both measures are significantly volatile.

Regarding external macro-financial variables, the average growth rates of the prices of copper, gold, and oil are around 0.2%, 0.6%, and 0.2%, respectively. All three commodity prices are quite volatile, but oil prices show the greatest dispersion. The average stock market return is 0.64% with a standard deviation of 4.2%.

Table 1: Macroeconomic and Financial Measures

Domestic Source		External
Macroeconomic	Financial	Source
Non-primary Manufacture (index)	Business Credit (const. prices)	Copper (price)
3-month Econ. Expectation (index)	Business Delinquency (%)	Gold (price)
Core CPI (%)	Household Delinquency (%)	Oil (price)
Total CPI (%)	Financial Mark-up	SP500 (index)
Interbank Interest Rate (%)	non-Core Funding	Real-state Price
Real Exchange Rate (index)	Liquidity Ratio (%)	Outstanding of Commercial Paper (const. prices)
Terms of Trade (index)	Stock Market Index	3-month LIBID Spread (bp.)
Non-traditional Exports (index)	CEMBI (bp.)	Long-Short run US Spread (bp.)
Industrial Inputs Imports (index)	Return Fund-2	Global Spread (bp.)
Household Credit	Exchange Rate	30-day Spread (bp.)
	EMBIG (bp.)	

5 Results

Figure (1) shows the estimated unobserved factors, which are interpreted as our uncertainty measures. It can be noticed that the evolution of the external uncertainty unobserved component coincides with important historical events. For instance, after September 2008 there is an abrupt surge in the external uncertainty measure, associated with the uncertainty created by the collapse of money and credit markets in developed countries. There was also a significant climb after end-2009, associated with the increase in Greece's default risk. Additionally, external uncertainty eased after the European authorities approved a bailout package for Spain in June 2012.

On the other hand, the unobserved component, labeled as domestic financial uncertainty, is correlated with external uncertainty but captures some particular dynamics of the Peruvian

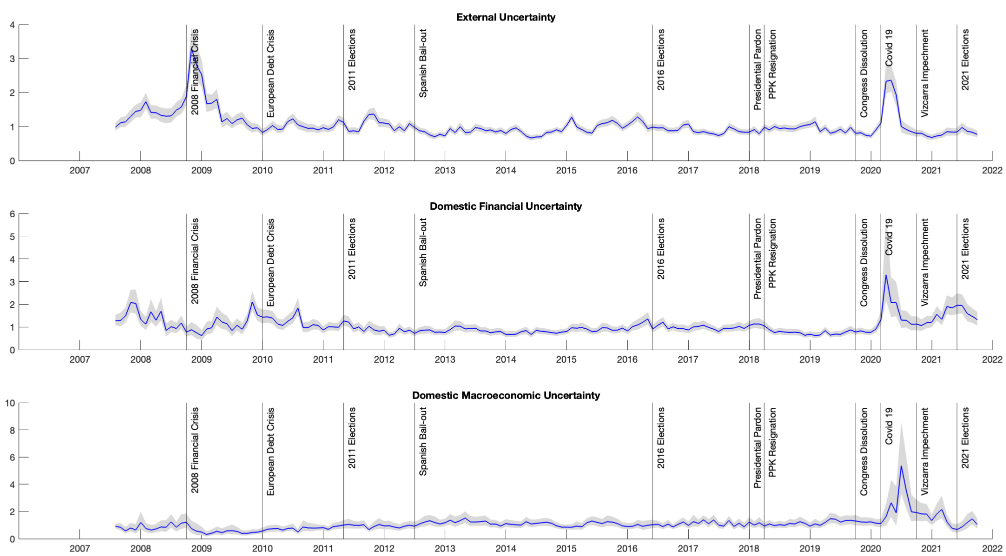
Table 2: Descriptive Statistics - Selected Variables

	Mean	Std. Deviation	Median	IQR
		Domestic Macroeconomic Variables		
ΔNon-primary Manufacture	0.2099	7.2094	0.3745	4.3150
Δ3-m Expectations	5.4364	11.5023	5.0000	14.6819
Core Inflation	0.1992	0.1187	0.1861	0.1181
ΔReal Exch.	0.0652	1.2393	0.0544	1.5063
ΔTerms of Trade	0.0672	2.2003	0.1080	2.6648
ΔHousehold Credit	1.0562	0.8932	1.0179	0.8555
		Domestic Financial Variables		
ΔBusiness Credit	1.1349	1.6321	1.0826	1.4850
ΔHousehold Delinquency	1.5625	11.2389	1.3557	6.7673
ΔBusiness Delinquency	0.4092	9.3322	1.6687	9.1567
ΔStock Market	0.1579	8.0146	0.1429	7.9203
ΔExchange Rate	0.1402	1.3081	0.0372	1.4434
EMBIG	180.3824	67.3806	165.0870	49.9666
Return Fund-2	6.1762	13.5805	5.3808	11.8816
		External Variables		
ΔCopper	0.1670	6.1136	-0.0324	6.6000
ΔGold	0.5737	3.3323	0.3525	4.3343
ΔOil	0.0219	11.1765	1.2385	9.5808
ΔSP500	0.6357	4.2165	0.9356	4.3497
ΔReal State Price	0.2167	0.6619	0.3458	0.6686
Long-Short US-Spread	1.1993	31.7085	-1.8235	44.7598
Global Spread	355.3118	92.6440	334.9300	84.6175

economy. It can be noted that, after the financial risks created by the GFC and the European crisis receded, a significant jump in domestic financial uncertainty took place, probably associated with the political instability created by the result of the first-round vote during the 2021 presidential election. There was also a significant jump in the run-up to the 2016 election and immediately after the introduction of pandemic-related containment measures.

Concerning the macroeconomic uncertainty unobserved component, its movement is less volatile than external and domestic financial uncertainty measures during 2007 and 2012, although it showed a slightly growing trend. Moreover, during the 2017-2019 episode of political instability, our macroeconomic measure tends to be more volatile. Additionally, it rises significantly in the months prior to the launching of President Vizcarra's congressional impeachment proceedings.

Figure 1: Estimated Unobserved Common Volatility Factors



Another important result is the estimation of effects on economic outcomes derived from unanticipated shocks on these uncertainty measures. It should be noted that, according to equation (4), the shocks on unobserved common factors are independent of structural shocks in the SVAR model (equation (1)). Unlike Carriero et al. (2018), in this study the ordering of variables matters partially, because of the block exogeneity restrictions we impose on equations (2), (4) and (1). For instance, a shock on the external uncertainty measure ($\ln(\xi_{E,t})$) affects contemporaneously the observable outcomes $\boldsymbol{y}_t$; and its effects, given that structural SVAR shocks are set to zero when uncertainty shocks occur, are quantified by the corresponding values in $\boldsymbol{A}^{-1}$. This is better visualized in the reduced form with stochastic volatility:

$$\boldsymbol{A}^{-1}\begin{pmatrix} \xi_{E,t}^{\beta_1^{E,E}} h_{1,t} & 0 & \dots & 0 & 0 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & \prod_{j\in\{fD,E\}} \xi_{j,t}^{\beta_{n_E+1}^{fD,j}} h_{n_E+1,t} & 0 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & 0 & 0 & \dots & \prod_{j\in\{mD,fD,E\}} \xi_{j,t}^{\beta_n^{fD,j}} h_{n,t} \end{pmatrix}\boldsymbol{\varepsilon}_t$$

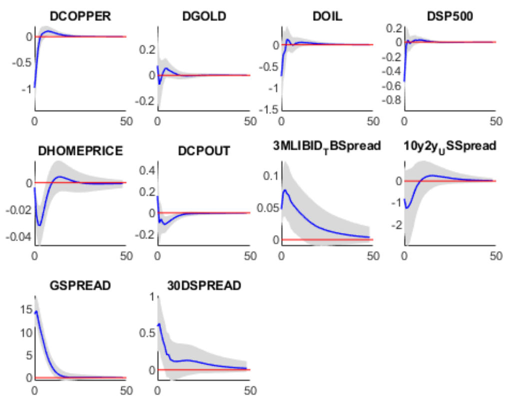
After the initial shock on the common factor uncertainty measure, the effects are transmitted to $\boldsymbol{y}_{t+h}$ through the corresponding coefficients in $\{\boldsymbol{\Pi}_k^{\boldsymbol{\xi}}\}_{k=1}^{p_\xi}$, as well as through the other conditional mean coefficients $\{\boldsymbol{\Pi}_k\}_{k=1}^{p}$. Moreover, it should be noted that shocks on uncertainty common factor measures do not only produce effects on conditional means but also on the conditional variances of the reduced-form errors, which magnifies the effects from shocks $\boldsymbol{\nu}_t$.

Response to an External Uncertainty Shock

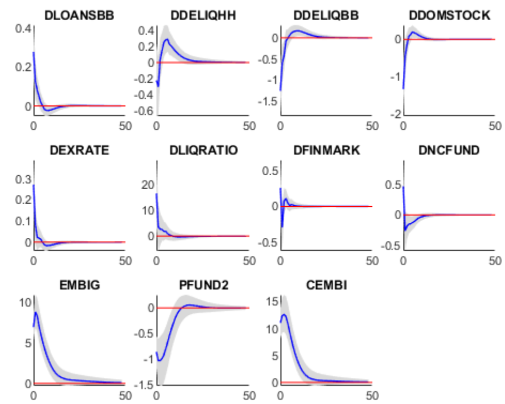
Figure (2) shows the response of the three sets of variables to a standardized shock on the external uncertainty unobserved common factor. Panel (2a) shows the response of external variables. It can be noted that an increase in external uncertainty produces a sharp fall in the international prices of commodities such as copper and oil, but their recovery is quite rapid. On the contrary, the fall in real estate prices, although not as deep, lasts longer than a drop in commodity prices. Additionally, there is a significant increase in liquidity spreads, such as the LIBID Spread and the spread of commercial papers up to 30 days, relative to the Fed rate and the Global spread, meaning that external uncertainty is translated to the demand for safe and liquid assets. It is worth noting the effect on the spread between long- and short-term U.S. Treasury bonds, whose median decreases in response to the rise in external uncertainty. This outcome may be explained by the *fly-to-quality* event.

The effects over domestic financial variables (2b) are in line with the findings in Bloom (2009); Jurado et al. (2015); Carriero et al. (2018) for a closed economy. The response of domestic stock market returns is a significant drop followed by a rapid recovery. Another measure of capital market returns is the performance of private pension funds. We took fund 2, which has a mixed risk profile. Its response to a climb in external uncertainty is a clear fall with an important level of persistence. Additionally, the rise in external uncertainty provokes a significant depreciation of the nominal exchange rate, consistent with the evidence on emerging

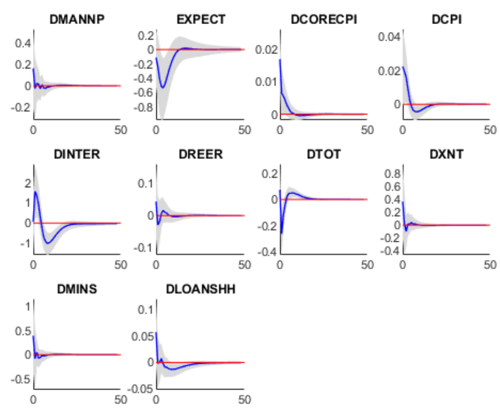
Figure 2: Response to Shocks on External Uncertainty Measures ($\ln \xi_{E,t}$)



(a) External Variables



(b) Domestic Financial Variables



(c) Domestic Macroeconomic Variables

market dynamics, where non-resident investors tend to shut down positions when uncertainty from external sources increases significantly. Both household and business delinquency rates rise in response to an external uncertainty shock. The initial drop in these rates is associated with the fact that external uncertainty shocks provoke a positive response in household and business loans.

Regarding the responses of domestic macroeconomic variables to an external uncertainty shock (2c), there is a clear fall in three-month-ahead economic expectations lasting several periods, with a non-contemporaneous maximum negative effect a few months after the external shock. In contrast, both core and total inflation rise. The surge in total inflation is in line with the sharp exchange rate increase. At the same time, the response of economic activity (measured by non-primary manufacturing, non-commodity exports, and industrial input imports) is not significant. There is also a significant drop in the terms of trade lasting a few periods, followed by a fast recovery to steady-state levels.

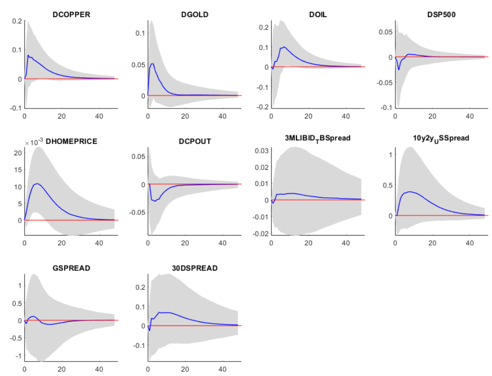
Response to a Domestic Financial Uncertainty Shock

Panel (3a) shows that the response of external variables to a shock on financial domestic uncertainty is not significant, especially the response of spreads and real estate prices. This is consistent with the block exogeneity restrictions we impose on SVAR and factor dynamics equations. Nonetheless, the response of international prices tends to be more significant and positive, probably because we do not impose restrictions on auto-regressive coefficients in SVAR equations.

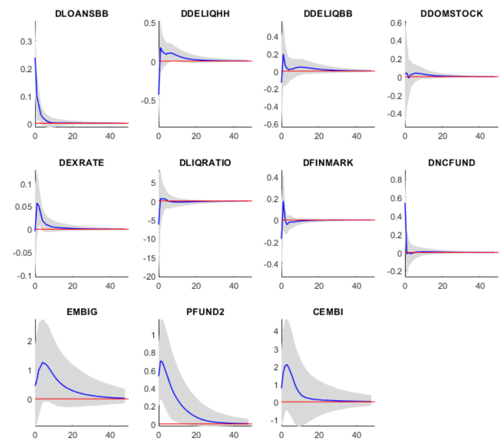
The effects on financial domestic variables (Figure (3b)) are similar to the responses to an external uncertainty shock in direction, but the magnitude is smaller. It can be noted that a rise in financial uncertainty leads to a nominal exchange rate depreciation, which, however, is at most one-third of the response to an external uncertainty shock. Additionally, the EMBIG and CEMBI spread measures have a positive response to an increase in financial domestic uncertainty; i.e., a rise in domestic uncertainty increases lending costs in domestic financial and credit markets. This is in line with the results obtained by Carriero et al. (2018) for the U.S. economy. Moreover, as in the case of a rise in external uncertainty, the response of delinquency rates is positive, although their confidence bands are significantly wider. The returns in the domestic stock market are nearly zero, while the yields of private pension funds with a moderate risk profile increase. This somewhat counter-intuitive result may be explained by the median response of the international prices of gold and copper, which is positive, and their confidence sets are, mostly, above zero.

Regarding the effects on domestic macroeconomic variables (3c), a financial uncertainty shock provokes a sharp fall in short-run economic expectations. In contrast with an external uncertainty shock, its effect peaks near the initial period and its recovery is faster. The effect on economic activity is negative, at least contemporaneously, with an almost immediate recovery. Core inflation drops slightly, although its confidence set is quite wide. At the same time, the effect on total inflation (including food and energy prices) is positive, with a large increase over the initial periods. This may be related to the increase in international oil prices and the exchange rate depreciation. The median response is positive, explained by the important jump in the total inflation rate. Finally, the median household loan response is negative and persistent.

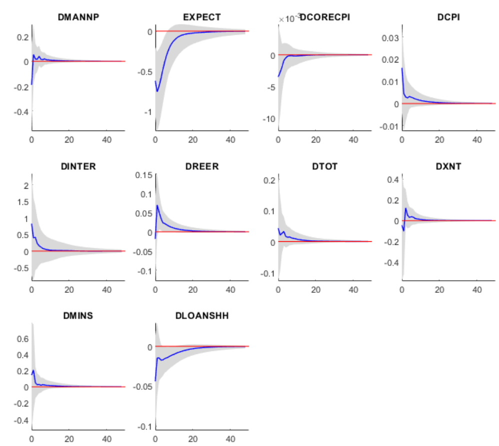
Figure 3: Response to Shocks in Domestic Financial Uncertainty Measures ($\ln \xi_{fD,t}$)



(a) External Variables



(b) Domestic Financial Variables



(c) Domestic Macroeconomic Variables

Response to a Domestic Macroeconomic Uncertainty Shock

Like in the case of a shock on domestic financial uncertainty, a surprise in domestic macroeconomic uncertainty should not produce any movement in external variables. Figure (4a) shows that the effects, although non-zero, are non-significant for all the variables, which is consistent with our restrictions.

Figure (4b) shows that a rise in domestic macroeconomic uncertainty produces a depreciation of the domestic currency, which peaks almost contemporaneously and declines rapidly back to its steady-state level. The response of the delinquency rate median response is positive, though not significant. Neither is the response of the domestic stock market. At the same time, unlike the effect of a domestic financial uncertainty surprise, the return of moderate-risk private pension funds drops when macroeconomic uncertainty rises. Moreover, the measure for domestic spreads increases (although their confidence bands are wider) but a large share of them are above zero. This is consistent with the results obtained by Carriero et al. (2018); Bloom (2009).

The effects on domestic macroeconomic measures are mixed (4c). The effect on short-run economic expectations is negative but not significant. At the same time, economic activity (non-primary manufacturing, non-commodity exports, and imports of industrial inputs) show a positive and contemporaneous response, with an immediate correction towards the steady-state level. The response of the total inflation measure is positive, mostly related to the nominal depreciation of the domestic currency. This also explains the increase in the interbank interest rate.

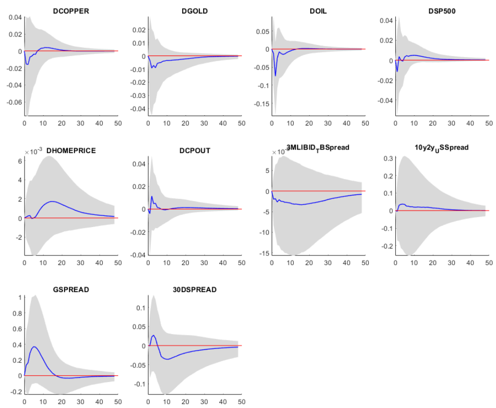
5.1 Fully Block Exogeneity Restrictions

From the above discussion, we find it unsatisfactory that external variables respond to shocks on domestic uncertainty measures. Hence, we impose more exclusion restrictions, but this time on the coefficient matrix $\mathbf{\Pi}_{j=1}^{p}$; i.e., the coefficients associated with the lagged values of observable vector values. In particular, we impose zero restrictions on the dynamic response of external variables to domestic macroeconomic and financial variables. Hence, $\mathbf{\Pi}_j$ has the following structure:

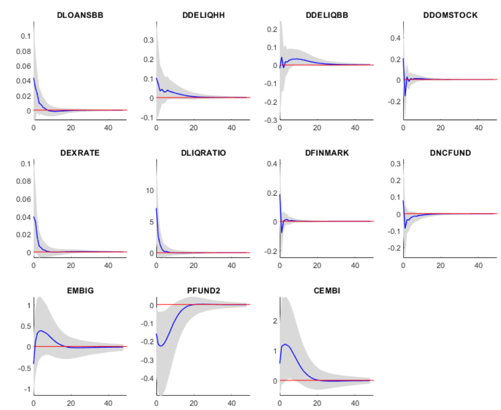
$$\mathbf{\Pi}_j = \begin{bmatrix} \boldsymbol{\pi}_{E\times E} & \mathbf{0}_{E\times fD} & \mathbf{0}_{E\times mD} \\ \boldsymbol{\pi}_{fD\times E} & \boldsymbol{\pi}_{fD\times fD} & \boldsymbol{\pi}_{fD\times mD} \\ \boldsymbol{\pi}_{mD\times E} & \boldsymbol{\pi}_{mD\times fD} & \boldsymbol{\pi}_{mD\times mD} \end{bmatrix}$$

Moreover, non-primary manufacturing may only capture developments in Peru's formal sec-

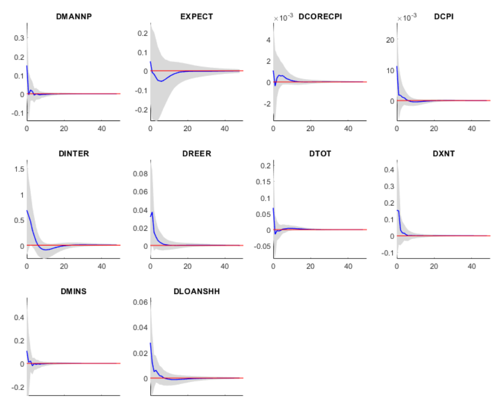
Figure 4: Response to Shocks in Domestic Macroeconomic Uncertainty Measures ($\ln \xi_{mD,t}$)



(a) External Variables



(b) Domestic Financial Variables

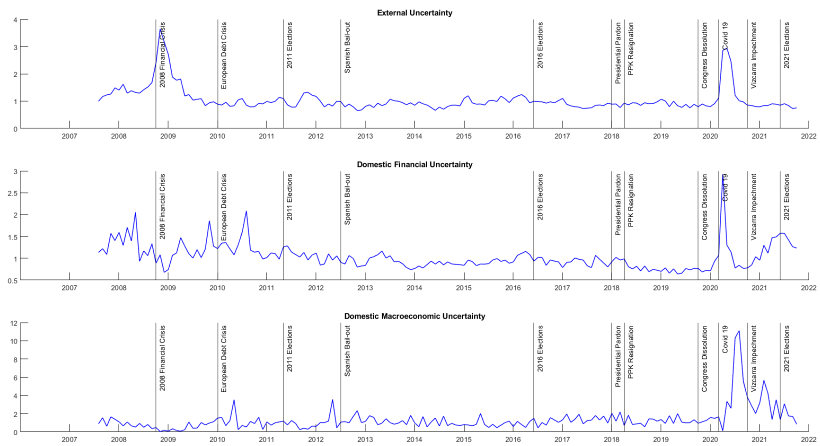


(c) Domestic Macroeconomic Variables

tor. In particular, non-primary manufacturing amounts to just 11% of Peru's GDP. Therefore, we add two measures for capturing domestic economic activity more accurately: real growth in consumption tax collections and growth in imports of capital goods (an important input for computing private investment). Figure (5) shows the median for the unobserved uncertainty measures. It can be noted that the trajectories of these new estimations and the former ones are quite similar. The only change has been the scale of the macroeconomic uncertainty measure.

Figures (6)-(7) show the responses to domestic financial and macroeconomic uncertainty measures. In this case, domestic uncertainty measures do not provoke a response from external

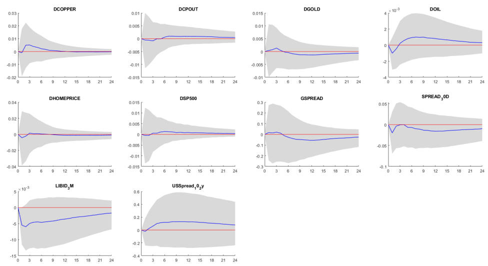
Figure 5: Uncertainty Measures with Extended Data Set



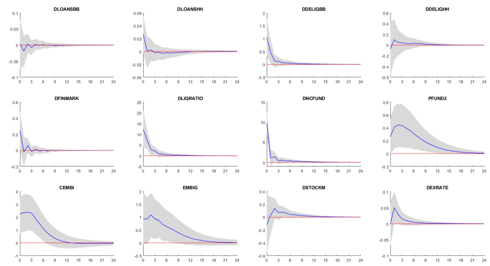
variables (at least, not a significant one for both measures). Hence, somehow we turned off the effects of external variables on domestic outcomes. Now, in the case of a shock that increases domestic financial uncertainty, the response of business loans seems to be non-significant, although the median response of household loans continues to be positive. The delinquency rate of business loans rises significantly, implying that credit conditions for firms will become tight. The liquidity ratio of deposit entities rises significantly, meaning that financial intermediaries have a preference for liquid assets. The rise of domestic spreads is similar to previous responses, as well as the response of the nominal exchange rate, which depreciates significantly. Moreover, the response of returns on the medium-risk pension fund portfolio continues to be positive, probably associated with the depreciation of the domestic currency and given that a significant share of this portfolio is invested in external assets.

Under this setup, the effects of macroeconomic uncertainty shocks differ from those estimated without the additional exogeneity conditions. The responses of household loans are non-significant, but business loans react positively. The delinquency rates for both types of loans increase. At the same time, the effects on domestic stock markets, the returns on private pension funds, and domestic spreads are negligible. In contrast, a rise in domestic macroeconomic uncertainty leads to a depreciation of the domestic currency. Regarding the responses of domestic macroeconomic measures, the urban unemployment rate reacts positively (i.e., unemployment increases). The effects on measures of economic activity (e.g., growth in non-primary

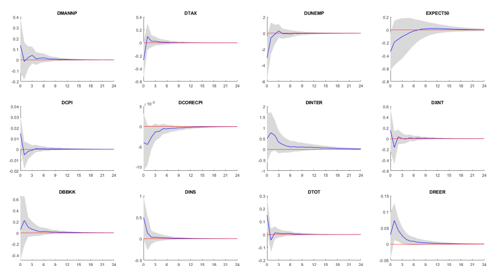
Figure 6: Response to Shocks in Domestic Financial Uncertainty Measures ($\ln \xi_{fD,t}$)



(a) External Variables



(b) Domestic Financial Variables



(c) Domestic Macroeconomic Variables

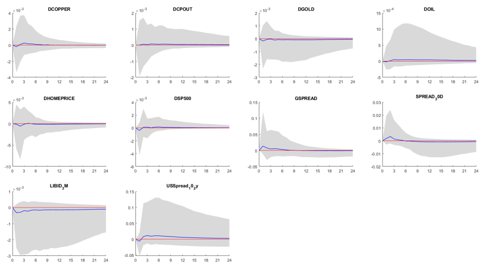
manufacturing or non-commodity exports), as well as on expectations, are not significant. However, tax revenues show a positive reaction; and growth in imports of industrial inputs and capital goods shows a negative, short-lasting, reaction. Additionally, the real exchange rate shows a significant positive response.

Importance of Uncertainty Shocks

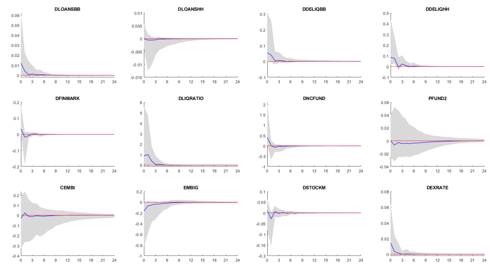
In order to identify which uncertainty shocks are more relevant in terms of their contribution to the variation in observable variables, we perform a historical decomposition analysis. Towards this end, we use the updated data set, which includes the additional economic activity variables. Moreover, since the effects of uncertainty shocks are of second order, their weight may be smaller compared with the group of shocks in the conditional mean. Hence, we take the difference between the observable variables and what is explained by structural disturbances in the SVAR model.

Figure (8) shows the relative importance of uncertainty shocks. External uncertainty shocks explain a significant share of spread measures and outstanding commercial papers. Regarding

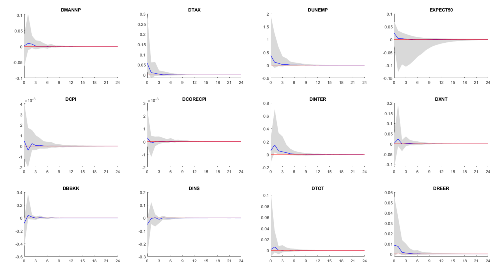
Figure 7: Response to Shock in Domestic Macroeconomic Uncertainty Measure ($\ln \xi_{mD,t}$)



(a) External Variables



(b) Domestic Financial Variables



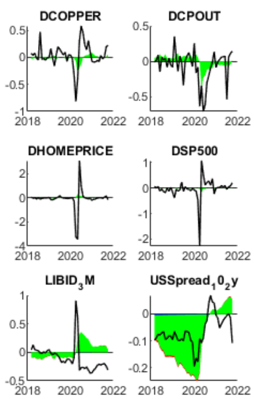
(c) Domestic Macroeconomic Variables

domestic financial measures, external uncertainty shocks are the most important in explaining domestic spread measures, exchange rate growth, and the returns on medium-risk private pension funds. They are also relevant in explaining growth in business loans. Domestic financial uncertainty shocks are less relevant but explain a significant share of non-core funding, the liquidity ratio, and returns on private pension funds. They also explain, although to a lesser extent, the variability of the nominal exchange rate.

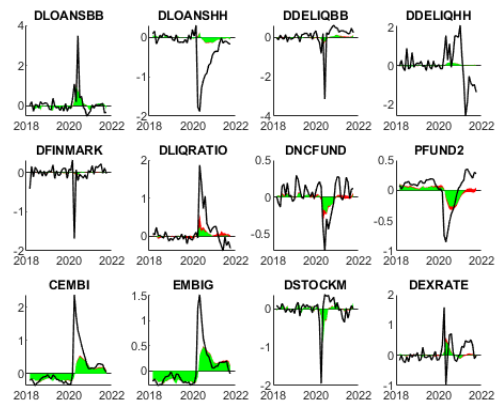
6 Conclusion

We estimate a model for measuring macroeconomic and financial uncertainty and its effects on the Peruvian economy, based on a large vector auto-regression model with stochastic volatility driven by common factors, extending the work by Carriero et al. (2018) to a small open economy where shocks affecting the real economy come from both external and domestic factors. Our results show that external financial uncertainty is an important driver of macroeconomic fluctuations; and that domestic uncertainty has a stronger impact on macroeconomic and financial

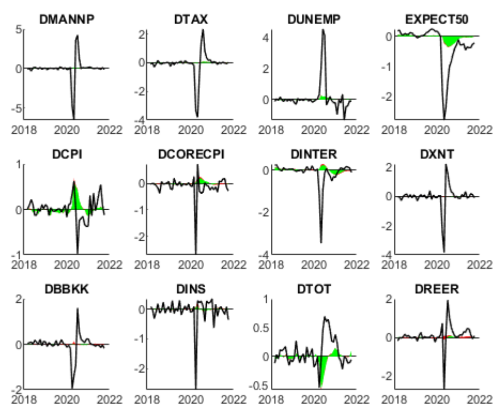
Figure 8: Historical Decomposition of Uncertainty Shocks



(a) External Variables



(b) Domestic Financial Variables



(c) Domestic Macroeconomic Variables

variables during electoral periods.

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