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Forecasting Peruvian Monetary Aggregates in a Nonlinear and Uncertain Environment

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Abstract

Making macroeconomic forecasts in a time-varying and uncertain environment is hard, especially for monetary aggregates such as credit, currency and total deposits. In this paper we employ a Bayesian Autorregressive Vector model with a time-varying mean and stochastic volatility to cover this task for the Peruvian economy. Results for different horizons exhibit a high level of predictive power. In addition, structural shocks are identified through zero and sign restrictions, i.e. supply and demand for credit by currencies together with other macroeconomic disturbances. Credit supply shocks in domestic currency expand credit and deposits in soles, reduce the *spread* between lending and deposit rates, produce a fall in credit in foreign currency, and an expansion of economic activity. Moreover, credit demand shocks in domestic currency produce an increase in the *spread* of lending and deposit rates, and a subsequent increase in economic activity.

JEL Classification: C53, E47, E51

Key words: Credit Demand, Credit Supply, Bayesian Vector Autorregressions, Stochastic Volatility

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1 Introduction

Producing macroeconomic forecasts in a time-varying and uncertain environment is today a huge challenge, especially in the case of monetary aggregates such as credit to the private sector, cash and total deposits. This task is even more difficult when there is a bi-monetary system, as in the Peruvian case, where financial intermediation activity is recorded in soles and dollars (partial financial dollarization). Peru is an economy that emerged from a traumatic episode of hyperinflation in the late 1980s, which triggered the partial dollarization structure, and reaching a single-digit year-to-year inflation levels in less than ten years. Nonetheless, dollarization was more persistent than inflation. After that, Peru adopted the inflation targeting scheme in 2002, along with a reference interest rate in 2003 as an operational target, and from that moment on the role of monetary aggregates began to be different, i.e. they are now determined by money demand, and money supply accommodates such that market interest rates are set in line with the reference rate[1]. In this context, our main purpose is to establish an empirical setup that allows us to forecast money aggregates and also to identify the main structural driving forces behind their dynamics over time. To the best of our knowledge, this is the first paper (at least for the case of Peru) that tackles both the theme of forecasting money aggregates and also to identify their structural factors[2].

The specification of an empirical macroeconomic model to forecast monetary aggregates within the Inflation Targeting scheme does not turn out to be a trivial task either, at least in the case of an emerging market economy (EME) such as Peru[3]. In particular, it is necessary to take into account the characteristics of the financial system of the economy under study. In first place, Peru has a bi-monetary Financial Intermediation system (Soles and USD for both credit and

[1]During the disinflation years the BCRP adopted the monetary base as the nominal anchor, and this was the operational target in the monetary policy scheme. As a result, monetary aggregates were mainly determined by supply and, to a lesser extent, demand factors. Furthermore, interest rates were determined endogenously as a function of the evolution of monetary aggregates, and these rates in some cases were extremely volatile (cite history book).

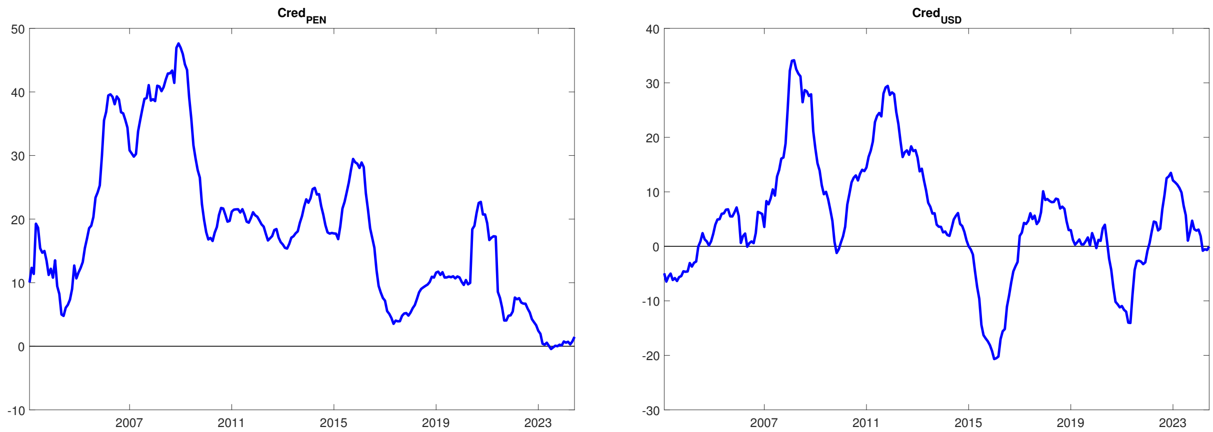
[2]The papers for the Peruvian case that address the issue of macroeconomic forecasts focus their attention on forecasting inflation and its determinants, taking the New Keynesian paradigm as a reference (Vega *et al.*, 2009; Winkelried, 2013; Aguirre *et al.*, 2023).

[3]The first forecasting model for the Peruvian Economy using bayesian techniques was implemented by Llosa *et al.* (2006).

deposits, see Figure 1), which turns the task of disentangling credit demand and supply shocks more challenging. As a matter of fact, we also need to measure financial conditions for the two currencies that co-exist in the system. Secondly, there exists a remarkable dollarization fall in the last 20 years, which can be related with an increasing relative confidence in the Peruvian Sol. The latter could also be considered as a structural change, and thus we cannot consider the traditional linear models with constant parameters as a proper strategy for both forecasting and performing structural impulse response analysis.

Figure 1: **Peru: YoY Growth in % - Credit to the Private Sector (2002-2024)**

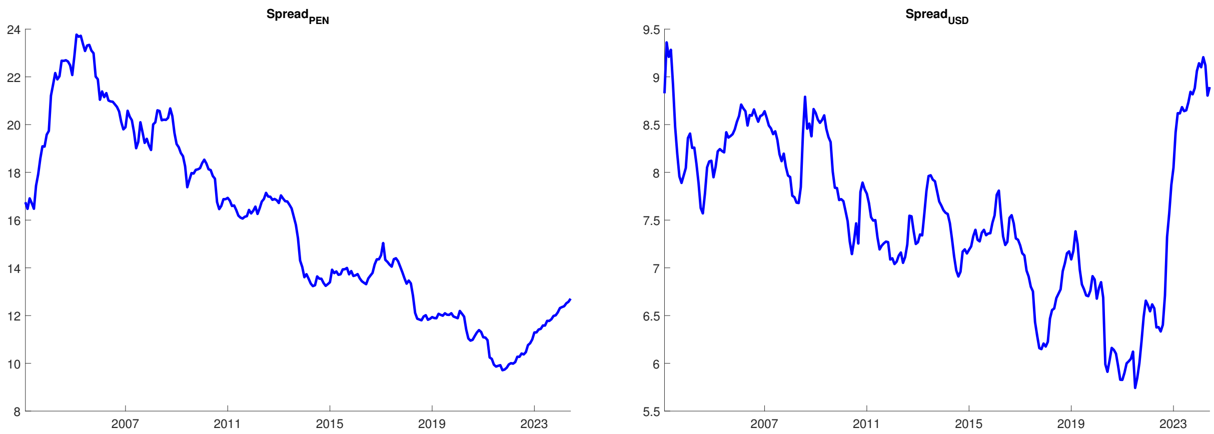
(a) Soles (PEN) (b) US$ (USD)



Furthermore, in order to accurately disentangle demand and supply forces, we need prices besides quantities, so that we explore interest rates data, i.e. lending and deposits rates. In first place we employ average interest rates associated with total balances of credit and deposits, and we compute the spread for both currencies (see Figure 2). We then merge this data with some other macroeconomic variables in the information set, so that we are able to produce aggregate credit forecasts.

Figure 2: **Peru: Interest Rate Lending-Deposit Spreads in % (2002-2024)**

(a) Soles (PEN) (b) US$ (USD)



In this paper we estimate a Bayesian Auto-regressive Vector model with a time-varying mean and stochastic volatility (TV-Mean-BVAR-SV) following Banbura and van Vlodrop (2018) for the period $2002-2024$, in order to prepare these forecasts for the Peruvian economy. The used methodology allows us to control for the data outliers associated with the $Covid-19$ pandemic (and other episodes) and, at the same time, to consider an expanded set of information, which includes the macroeconomic expectations survey as in Pérez Forero (2021). Likewise, the forecasts obtained can be free or conditioned to a particular macroeconomic scenario, which is also useful as a starting point for a Financial Programming exercise.

In addition, taking into account that the dynamics of credit to the private sector is explained by different macroeconomic and financial shocks, i.e market forces such as aggregate supply and demand, as well as by monetary policy actions and other factors. Given the estimated model, we proceed to identify structural shocks through the imposition of zero and sign restrictions. In particular, this work identifies credit supply and demand shocks by currencies and together with other traditional macroeconomic shocks (monetary policy, aggregate demand and supply, etc.). Aggregate supply and demand shocks, exchange rate shocks, together with monetary policy shocks, produce the usual effects and in line with previous empirical evidence. Furthermore, credit supply shocks in domestic currency expands total credit and deposits in soles, reduces the spread between lending and deposit rates, produces a fall in credit in foreign currency, and an expansion of economic activity that is subsequently reflected in an increase in inflation and the response of the central bank by raising its interest rate. Moreover, a shock demand for credit in national currency produces an increase in the spread of active and passive rates, and a subsequent increase in economic activity. On the other hand, a credit supply shock in foreign currency expands credit and liquidity in said currency, reduces the spread between lending and deposit rates, and their effect on economic activity is also positive. Finally, the credit demand shock in foreign currency also produces an increase in the spread between active and passive rates and an expansion of economic activity.

Literature Review

Choy *et al.* (2015) provide a structural decomposition of active lending rates. The latter analysis provides an explanation for the observed heterogeneity in interest rates across different types of credit, since they depend on the risk level and operational expenditures. In addition, Céspedes (2017a) explores the heterogeneity in the demand for credit across individuals using credit registry data for Peru, and Céspedes (2017b) extends the previous analysis to explore the demand for credit in each currency (soles and dollars).

During the period between 2014 and 2018 the BCRP applied a strict de-dollarization program imposiong additional reserve requierements. The effects of these policy measures were highly significant, reducing the dollarization rate from 45% to less than 30%. As a result, the peruvian economy is today more resilient to foreign financial shocks reflected in the exchange rate. Empirical evidence on the effect of these measures can be found in Castillo *et al.* (2015), Choy (2015) and Contreras *et al.* (2018).

Furthermore, during the Covid-19 pandemic episode the BCRP implemented Credit Policy program (Reactiva Perú), which was a policy measure without any precedent in Peru. The credit policy program had the Government guarantee, and the liquidity injection was implemented using the latter together with the previous credits as collateral. The main description of this program, can be found in Montoro (2020), and the empirical studies that quantify the effect of these policy measures can be found in Acurio *et al.* (2023) and Burga *et al.* (2023). Finally a theoretical approach for characterizing these type of programs can be found in Pozo and Rojas (2021).

In terms of methodology, we employ the Bayesian Vector Autorregressive model (BVAR) with a time Varying Mean and with Stochastic Volatility proposed by Banbura and van Vlodrop (2018) and used in a previous smaller exercise for Peru by Pérez Forero (2021). In addition, we impose a mixture of Zero and Sign Restrictions for structural shocks identification. Some references in mixing these two types of restrictions can be found in Canova and Pérez Forero (2015) and Arias *et al.* (2018). In particular, recent references in disentangling Credit Demand and Supply in BVARs using Zero and Sign Restrictions can be found in Balke *et al.* (2021) and Büyükbaşaran *et al.* (2022).

Main Results

Traditional macroeconomic shocks, such as supply and demand, along with monetary policy and exchange rate shocks, produce the usual textbook effects, in line with previous empirical evidence for the Peruvian economy. On the one hand, the credit supply shock in soles expands credit and liquidity in that currency, reduces the spread between lending and deposit rates, produces a drop in credit denominated in foreign currency, and produces an expansion of the economic activity. These effects are subsequently reflected in an increase in inflation and the response of the central bank by raising its interest rate. A credit demand shock in soles produces an increase in the spread of lending and deposit rates, and a subsequent increase in economic activity. A credit supply shock in foreign currency expands credit and liquidity in that currency, reduces the spread between lending and deposit rates, and its effect on economic activity is also positive.

Finally, credit demand shocks in foreign currency also produce an increase in the spread between lending and deposit rates, and an expansion of economic activity. The historical decomposition shows that the last deceleration in aggregate credit in domestic currency is explained by negative exchange rate shocks, negative aggregate demand and supply shocks, and also because of the monetary tightening. The historical decomposition also shows that the last deceleration in aggregate credit in foreign currency is explained by different structural factors.

The document is organized as follows: section 2 describes the empirical model used for the analysis, section 3 describes the empirical application and discusses the main results, section 4 presents alternative specifications as robustness checks, and section 5 concludes.

2 The empirical Model

2.1 Main Setup

In this section we closely follow the setup of Banbura and van Vlodrop (2018)[4]. Consider the Bayesian Vector Auto-regressive model (BVAR) model with $p \geq 1$ lags in monthly frequency:

$$y_t - \tau_t = \sum_{k=1}^{p} B_k \left(y_{t-k} - \tau_{t-k} \right) + \varepsilon_t, \qquad \varepsilon_t \sim N\left(0, H_t\right) \tag{1}$$

$$\tau_t = \tau_{t-1} + \eta_t, \qquad \eta_t \sim N\left(0, V_t\right) \tag{2}$$

$$z_t = \tau_t + g_t, \qquad g_t \sim N\left(0, G_t\right) \tag{3}$$

where y_t is the $(N \times 1)$ vector of macroeconomic and financial variables, z_t is the $(N_Z \times 1)$ vector that includes the long-term expectations, and τ_t is the $(N \times 1)$ vector that includes the time-varying means for each variable in y_t. Equation (1) represents the typical dynamic Vector Auto-regressive system used for macroeconomic forecasting but with a time-varying mean τ_t, which has an error term vector ε_t that is $(N \times 1)$ and normally distributed with a time-varying covariance matrix H_t that is $(N \times N)$. The matrices $\{B_k\}_{k=1}^{p}$ are also $(N \times N)$. In addition, H_t is given by $H_t = A^{-1} \Lambda_t \left(A^{-1} \right)'$, where A is a $(N \times N)$ lower triangular matrix with the main diagonal governed by ones (with free parameters denoted by α[5]), and where Λ_t is a $(N \times N)$ diagonal matrix that includes the time-varying volatilities in its main diagonal for each variable in y_t. A typical assumption for latent variables when specifying state space systems is that they can follow a random walk *a priori*, as it is the case for τ_t in equation (2). Finally, V_t and G_t are

[4] See also Pérez Forero (2021) for a previous application for the Peruvian economy with a smaller variable set.

[5] Here we use the notation of Amisano and Giannini (1997), such that $vec\,(A) = S_A \alpha + s_A$, with S_A and s_A being rectangular matrices governed by zeros and ones.

also diagonal matrices that include the time-varying volatilities in their main diagonal for each τ_t and z_t, respectively. Regarding the log-volatilities, all of them follow a random walk process as specified in equation (4).

$$x_t = x_{t-1} + \epsilon_t, \qquad \varrho_t \sim N\left(0, \phi_{j,i}\right) \tag{4}$$

where x_t is the log of a particular element of the main diagonal of $j = \{H, V, G\}$ and for each $i = 1, \ldots, dim\left(diag\left(j\right)\right)$

2.2 Bayesian Estimation

2.2.1 Prior specification

Consider the complete parameter set of the model $\Theta = \left\{\Lambda^T, V^T, G^T, \phi_H, \phi_V, \phi_G, B, \alpha\tau^T\right\}$, where the superscript T denotes the full time series of the parameter block. Moreover, B represents the BVAR matrix coefficients such that $B = [B_1, \ldots, B_p]$, α is the vector of free parameters related with matrix A.

For the BVAR coefficients $\beta = vec(B)$ we take an independent normal prior, i.e. a conjugated prior:

$$p\left(\beta\right) = N\left(\mu_B, \lambda_0 \Omega_B\right) \tag{5}$$

with μ_B as the common mean and λ_0 as the overall tightness parameter. Since me assume that the model is stationary in mean, and because the variables included in the model are transformed to be stationary, we set $\mu_B = 0_{dim(\beta)}$. The covariance matrix Ω_B takes the form of the typical Minnesota prior (Litterman, 1986), i.e. $\Omega_B = diag\left(\omega_{ij,l}\right)$ such that

$$\omega_{ij,l} = \begin{cases} \frac{1}{l^{\lambda_3}} & , i = j \\ \frac{\lambda_1}{l^{\lambda_3}} \left(\frac{\widehat{\sigma}_j^2}{\widehat{\sigma}_i^2}\right) & , i \neq j \\ \lambda_2 & , exogenous \end{cases} \tag{6}$$

where

$$i, j \in \{1, \ldots, M\} \text{ and } l = 1, \ldots, p$$

and $\widehat{\sigma}_j^2$ is the variance of the residuals from an estimated $AR(p)$ model for each variable $j \in \{1, \ldots, M\}$.

We set the parameters $\lambda_0 = 0.2$, $\lambda_1 = 0.5$, $\lambda_2 = 1$, $\lambda_3 = 2$, taking the benchmark values of Doan *et al.* (1984) (see also Canova (2007)) except the one for the exogenous component λ_2, which is typically set to $10,000$. We do not consider this value since this was set for a constant intercept, and the context is completely different is this model. In addition, we do not estimate these hyper-parameters for the Peruvian case. One possible extension could be to follow Giannone *et al.* (2015) and estimate the posterior of the overall tightness parameter λ_0 using a metropolis-hastings step, and another one could be to expand the Gibbs Sampling routine using a hierarchical structure. Both approaches would be a natural extension of the presented setup. We could also explore the sensitivity of the results using different parameter configurations[6].

The prior distribution for the covariances parameters included in matrix A could be specified as in Canova and Pérez Forero (2015)[7], i.e. we extract the vector of parameters as follows:

$$vec\,(A) = S_A \alpha + s_A \tag{7}$$

Thus, it is then possible to specify a prior for the entire vector such that:

$$\alpha \sim N\left(\mu_\alpha, \Omega_\alpha\right) \tag{8}$$

where we assume $\mu_\alpha = 0_{dim(\alpha)}$ and $\Omega_\alpha = 10 \times I_{dim(\alpha)}$.

In the case of the stochastic volatility processes, we need to specify the distribution of the initial point and the prior distributions for the variance parameters ϕ governing the amount of time

[6] These results are available upon request.

[7] See also Amisano and Giannini (1997) for a detailed description of this strategy for extracting the vector α.

variation in the process as follows:

$$ln\sigma^2_{j,i,p+1} \sim N\left(0, \upsilon^2_j\right), \phi_{j,i} \sim IG\left(d_{\phi_j} \times \underline{\phi}_{j,i}, d_{\phi_j}\right), i = 1, \ldots, dim\left(diag\left(j\right)\right) \tag{9}$$

Specifically, we set $\nu_j = 100$, i.e. we treat this as a diffuse filter since the prior law of motion of volatility is a random walk. In addition, we set $d_{\phi_j} = 10$ and $\underline{\phi}_{j,i} = 0.1$ and $j = \{H, V, G\}$. A similar parametrization can be found in Carriero *et al.* (2016).

Finally, for the case of the full path of the time-varying mean τ^T, we specify the prior for the initial point in a similar way:

$$\tau_{p+1} \sim N\left(\mu_\tau, \Omega_\tau\right) \tag{10}$$

In this case, since this is also a diffuse filter, we set $\mu_\tau = 0_{dim(\tau)}$ and $\Omega_\tau = 100 \times I_{dim(\tau)}$.

2.2.2 Reduced Form - Gibbs Sampling Algorithm

Using the Bayes' theorem we can characterize the posterior distribution for the whole set Θ conditional on the dataset:

$$P\left(\Theta \mid y^T, z^T\right) \propto P\left(y^T, z^T \mid \Theta\right) P\left(\Theta\right) \tag{11}$$

where $P\left(y^T, z^T \mid \Theta\right)$ is the likelihood function and $P\left(\Theta\right)$ is the prior distribution of parameters.

Following the usual practice in Markov Chain Monte Carlo (MCMC) methods, we can specify split the full parameter set Θ into different blocks such that we can use Gibbs Sampling, which in general is more efficient than trying to maximize equation (11) by brute force. Denote also Θ/χ as the parameter set Θ excluding the block χ. Then, the following algorithm is used to sample the posterior distribution (see details in Appendix **??**).

Set $k = 1$ and consider K as the total draws. Set an initial condition Θ_0 and then:

1. Draw $p\left(\Lambda^T \mid \Theta/\Lambda^T, y^T, z^T\right)$: State Space (Kalman Filter) - Volatility

2. Draw $p\left(V^T \mid \Theta/V^T, y^T, z^T\right)$: State Space (Kalman Filter) - Volatility

3. Draw $p\left(G^T \mid \Theta/G^T, y^T, z^T\right)$: State Space (Kalman Filter) - Volatility

4. Draw $p\left(\phi_{j,i} \mid \Theta/\phi_{j,i}, y^T, z^T\right)$: Inverse-Gamma simulation, $j = \{H, V, G\}$ and $i = 1, \ldots, dim\left(diag\left(j\right)\right)$

5. Draw $p\left(B \mid \Theta/B, y^T, z^T\right)$: Truncated Linear Regression

6. Draw $p\left(\alpha \mid \Theta/\alpha, y^T, z^T\right)$: Linear Regression

7. Draw $p\left(\tau^T \mid \Theta/\tau^T, y^T, z^T\right)$: State Space (Kalman Filter)

8. Draw $p\left(S_{j,i}^T \mid \Theta/S_{j,i}^T, y^T, z^T\right)$: Discrete Variable, $j = \{\Lambda, V, G\}$ and $i = 1, \ldots, dim\left(diag\left(j\right)\right)$

9. If $k < K$, set $k = k + 1$ and go back to step 1.

where M is either N or N_Z. We select the block order such that it considers the correction of Del Negro and Primiceri (2015), i.e. we first need to sample the volatilities, then the constant parameters and finally the latent variables of the system. We also consider the auxiliary discrete variables (S_i^T, in line with the methodology proposed by Kim *et al.* (1998). A complete cycle of the steps 1 to 7 gives use one iteration k, and we repeat this process $K = 50,000$ times discarding the first $25,000$ draws in order to eliminate the effect of the initial condition Θ_0. We also use a thinning factor of 10, i.e. we discard 9 draws for each group of 10, so that we can also rule out any possible auto-correlation across draws, thereby ensuring the convergence to the ergodic distribution.

3 Empirical Application

3.1 Peruvian Data

In this section we present the estimates of the system of equations (1) – (2) – (3) using Peruvian Macroeconomic and Financial data. We select the most relevant variables for the Peruvian economy and for the Inflation Targeting period, i.e. from 2002 to 2024, and we employ data in monthly frequency. In first place, we include headline inflation and GDP growth, bot in year-to-year percent changes. These variables are the most representative indicators for the macroeconomy. Then, in order to accurately characterize the credit determination, we consider YoY growth rate of aggregate credit to the private sector in soles (PEN) and US$, and the spread of Lending-Deposits interest rates, i.e. the variables depicted in figures 1 and 2, respectively. In addition, we include the principal funding source of credit in Peru, i.e. the YoY growth rate of deposits in soles (PEN) and US$ (USD), as well as the cash in circulation. Finally, we include the interbank interest rate, which is relevant for the monetary policy identification, and the exchange rate YoY depreciation (soles against US$), since Peru is a small open economy and with partial dollarization in the financial system. The full set of variables for the vector y_t is depicted in Figure 3.

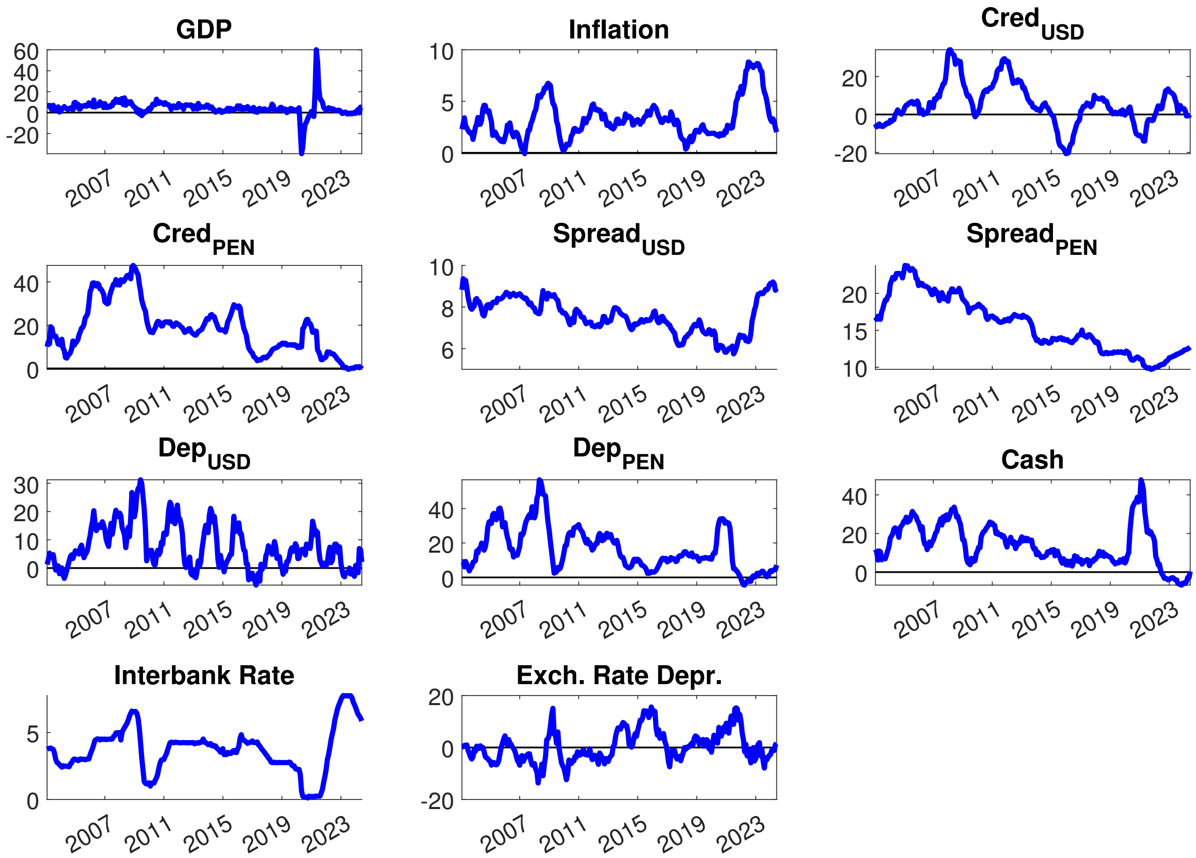


Figure 3: Peruvian Macroeconomic Data (2002.01-2024.05) - y^T

Moreover, following Banbura and van Vlodrop (2018), we also consider data from a survey of expectations. In this case, we consider the long term expectations of GDP growth, Inflation and the exchange rate from the BCRP Survey[8], in line with Pérez Forero (2021). Finally, we include the higher term available interest rate from the Central Bank securities' yield curve.

[8]See details in https://www.bcrp.gob.pe/estadisticas/encuesta-de-expectativas-macroeconomicas.html

In this case, the full set of variables for the vector z_t is depicted in Figure 4. Regarding this data set, two aspects deserve particular attention. First, data can have missing values, and secondly, some variables in y_t do not have a survey of expectations counterpart in z_t. This is not a problem for the estimation of the model, since we use the Kalman Filter at each point in time, and whenever there is no data the Kalman gain is zero. Of course, at the end of the day the data set z^T contributes significantly to the estimation of τ^T, so that for the variables with survey data the posterior estimates are more precise relative to the ones of the remaining variables.

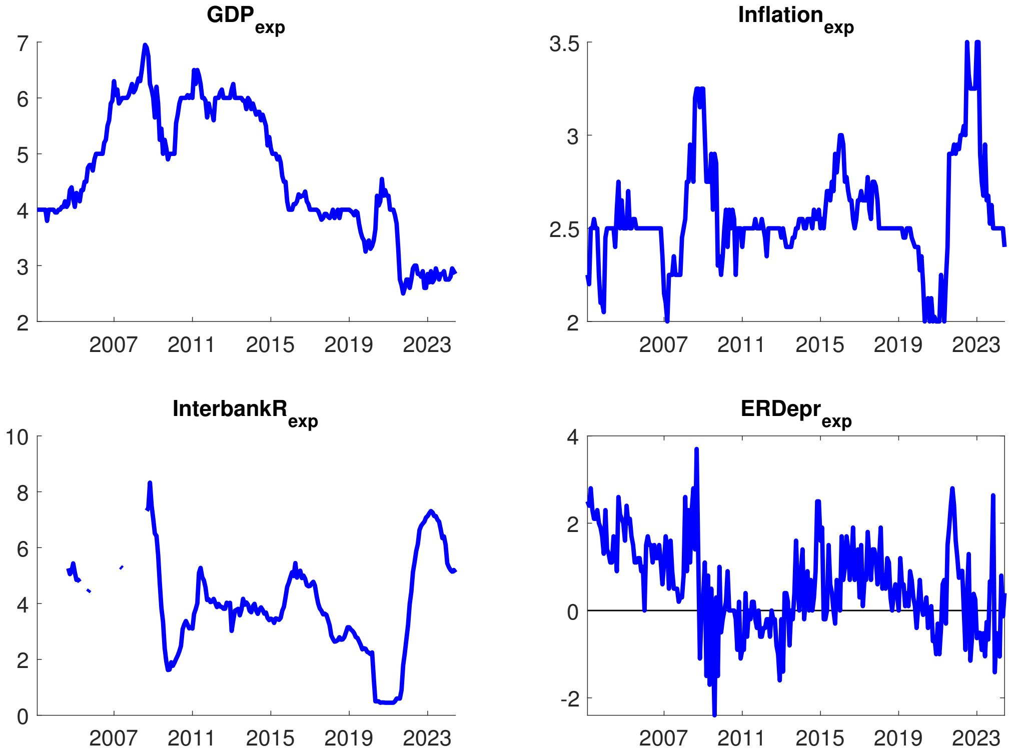
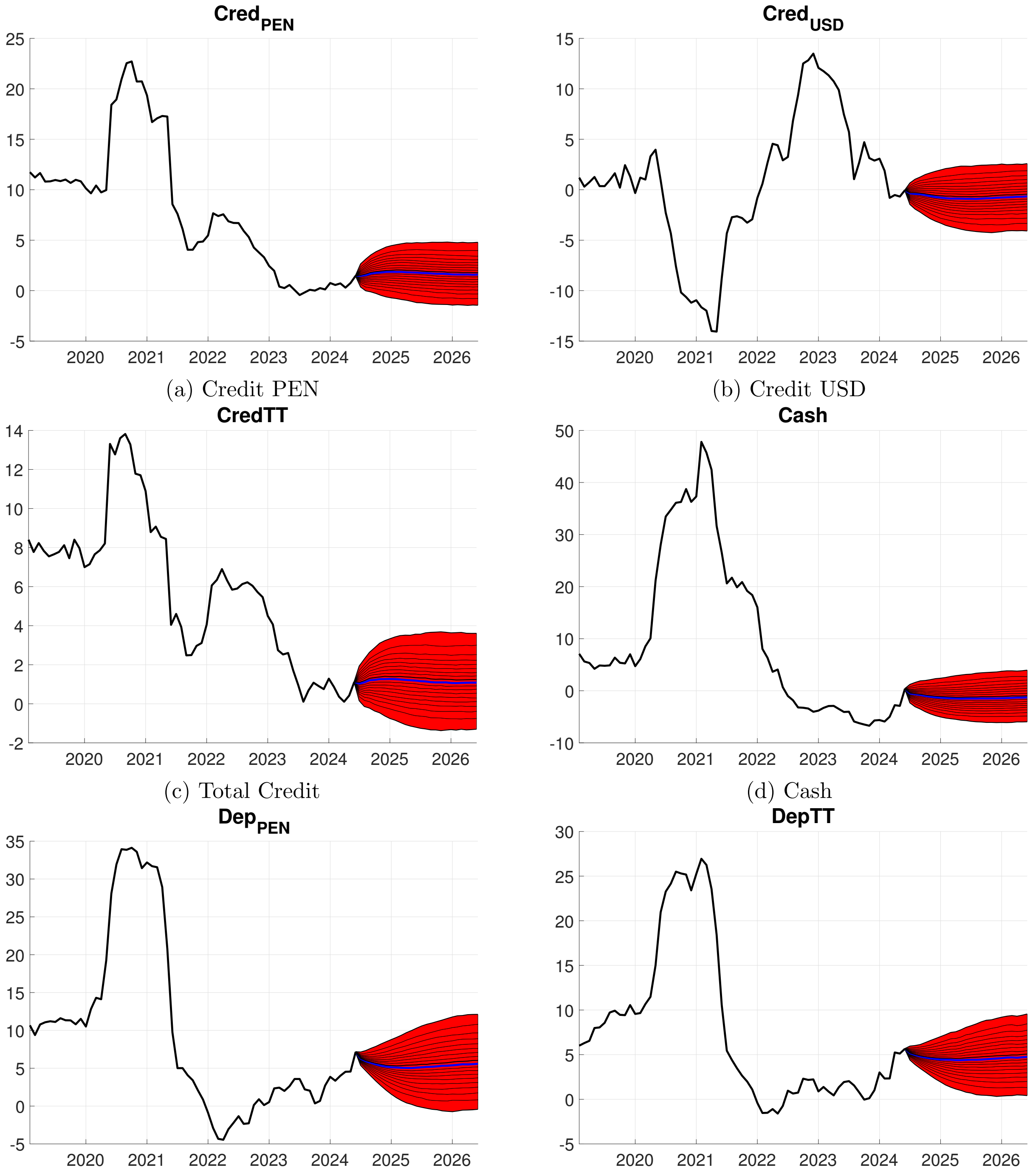


Figure 4: Peru: Long-Term Expectations Survey Data (2002.01-2024.05) - z^T

3.2 Forecasting Monetary Aggregates

In this section we present the main forecast output of the model. We consider May 2024 as the initial point for performing the forecasting exercise. Using the posterior estimates of each of the parameter blocks in Θ, we compute the unconditional forecast for each of the variables of interest, and the results for the median value and the fan charts are depicted in Figure 5[9].



(a) Credit PEN (b) Credit USD

(c) Total Credit (d) Cash

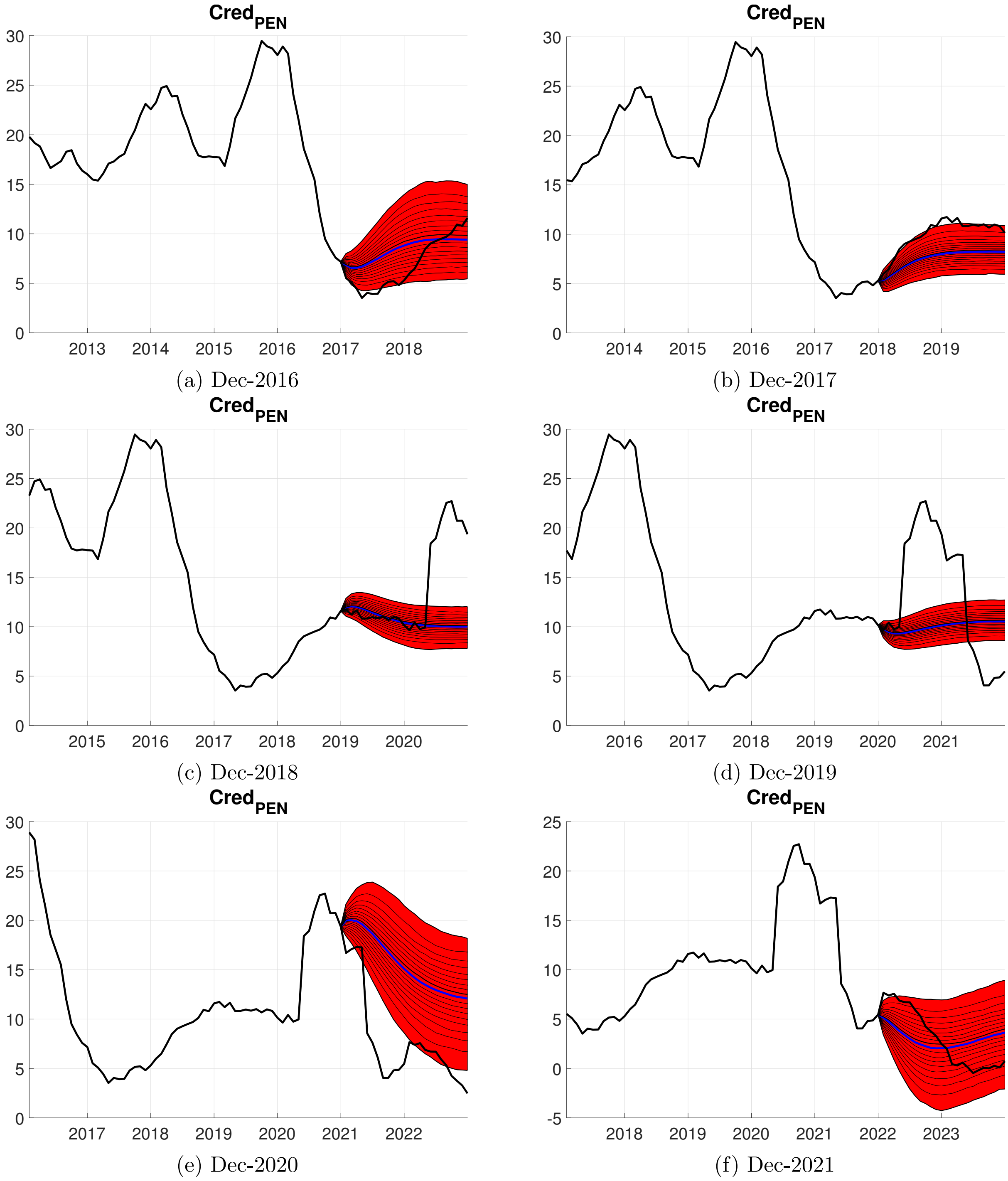
(e) Deposits PEN (f) Total Deposits

Figure 5: Money Aggregates YoY Growth Forecast - Fan charts of 95% of probability

[9]The Forecasting algorithm takes into account all the non-linearities considered in the model specification, i.e. it forecasts the volatilities, then forecasts the time varying mean τ_t, and finally forecasts the observables y_t and z_t. Computation details can be found in Appendix A.1.

Given the bayesian estimation of the model parameters, and the accurate randomization of shocks when performing the recursive forecasting exercise, we are able to quantify the uncertainty associated with the object of interest, which is a nonlinear function of model parameters and states. Since shocks are normally distributed, then the larger the horizon the higher the uncertainty forecast. In addition, recalling the fact that the model is nonlinear and includes a time varying mean τ_t, then the model does not revert to the constant sample mean, and instead converges to the forecasted path of $\tau^{T+1:T+\overline{H}}$. This is a crucial property of this model that potentially makes it superior relative to a constant coefficients BVAR model.

Predictive Power A plausible validation of the forecasts is to consider the predictive power of the model. For that purpose, we run the forecasts cutting the sample at different years, so that we can compare them with actual data. That is, we set the end-of-sample points of December from 2016 to 2021 as a benchmark for comparison, and we consider $\overline{H} = 24$, i.e. a 2-years forecast horizon. Then, we juxtapose the fan chart of the posterior forecasts and the actual data in order to contrast how far is the observed data with respect to their estimated values. It turns out that, with the exception of the Covid-19 pandemic episode, the presented model is capable of capturing the future path of credit YoY growth in both currencies as it is shown in Figures 6 and 7, as well as for other money aggregates (see Appendix *B*.).



(a) Dec-2016

(b) Dec-2017

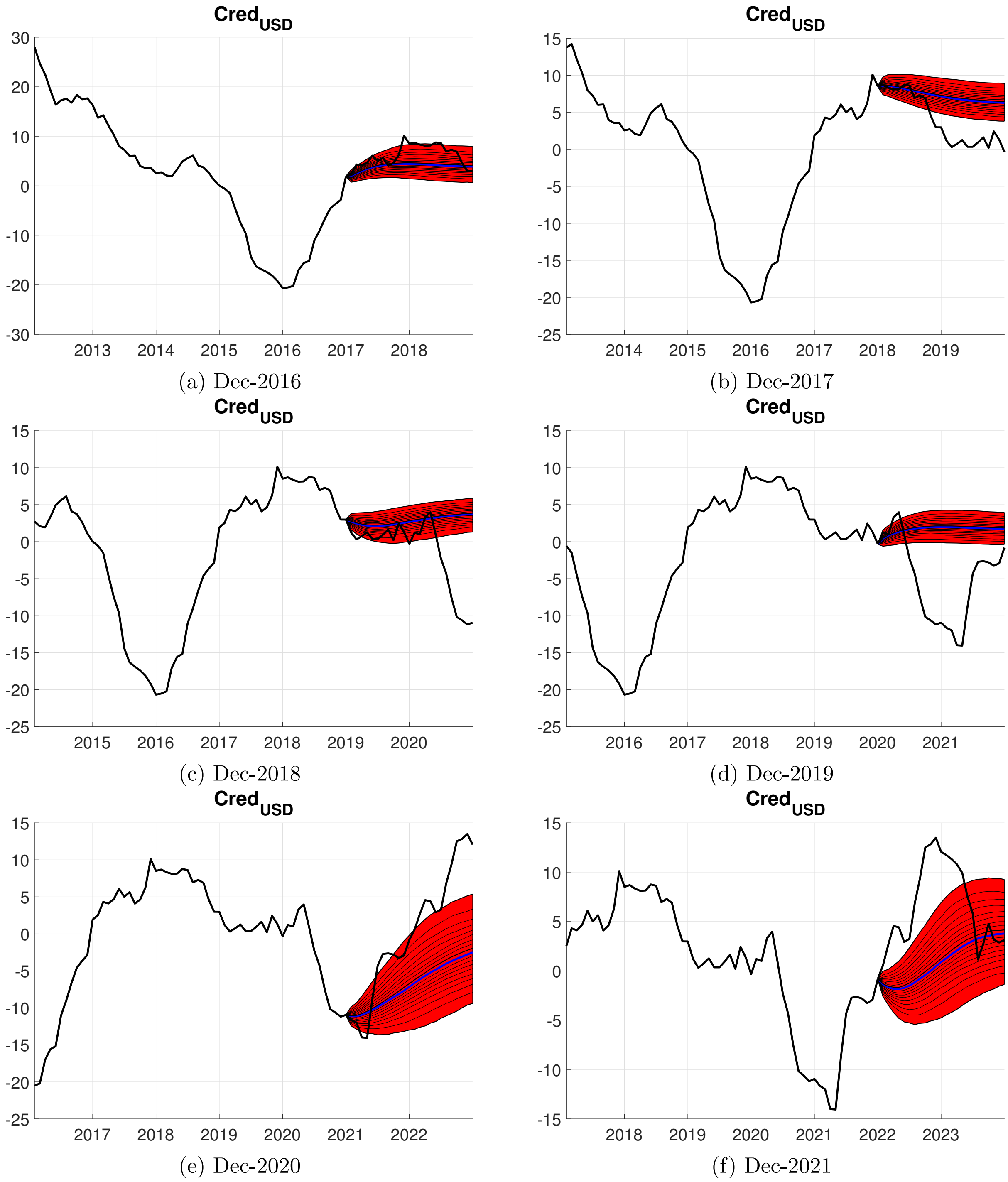
(c) Dec-2018

(d) Dec-2019

(e) Dec-2020

(f) Dec-2021

Figure 6: Credit PEN YoY Growth Forecast - Fan charts of 95% of probability



(a) Dec-2016 (b) Dec-2017

(c) Dec-2018 (d) Dec-2019

(e) Dec-2020 (f) Dec-2021

Figure 7: Credit USD YoY Growth Forecast - Fan charts of 95% of probability

3.3 Structural Shocks Identification

After computing the reduced-form parameters, we are ready to identify structural shocks. For that purpose, we impose a mixture of Zero and Sign Restrictions for credit demand-supply shocks (Balke *et al.*, 2021; Büyükbaşaran *et al.*, 2022), in our case for both domestic (PEN) and foreign (USD) currency. In addition, we impose restrictions in order to identify other traditional macroeconomic shocks, such as: i) monetary policy, ii) aggregate demand, iii) aggregate supply, and iv) exchange rate shocks, so that it will be possible to get the historical decomposition of aggregate credit in each currency. The full set of restrictions are summarized in Table 1 and the algorithm to compute impulse responses can be found in Appendix *A.2*.

Now we proceed to explain the economic intuition behind the identification restrictions for each structural shocks. In first place, we consider *slow* variables as the ones that do not react contemporaneously to other shocks except of their specific one. In this group of variables we include the GDP growth, the Headline Inflation, and the Aggregate Credit in both domestic (PEN) and Foreign (USD) currency. We assume that each structural shock is orthogonal (independent) of the remaining shocks in the system, so that we can interpret the associated impulse responses of each one as an estimated average causal effect for the period 2002-2024.

Var / Shock	**Mon. Policy**	**Aggr.Demand**	**Aggr.Supply**	**Cred. S (PEN)**	**Cred. D (PEN)**	**Cred. S (USD)**	**Cred. D (USD)**	**Exch. Rate**	**Cat.**
GDP	≤ 0	> 0	≤ 0	≥ 0	≥ 0	≥ 0	≥ 0	?	S
Inflation	≤ 0	≥ 0	> 0	≥ 0	?	≥ 0	?	≥ 0	S
Credit in USD	?	≤ 0	?	?	?	> 0	≥ 0	?	S
Credit in PEN	≤ 0	?	?	> 0	≥ 0	?	?	?	S
Spread in USD	?	?	?	?	?	≤ 0	> 0	?	F
Spread in PEN	?	?	?	≤ 0	> 0	?	?	?	F
Dep. in USD	?	?	?	?	?	?	?	?	F
Dep. in PEN	≤ 0	?	?	?	?	?	?	?	F
Cash in PEN	?	?	?	?	?	?	?	?	F
Interbank Rate	> 0	≥ 0	≥ 0	?	?	?	?	≥ 0	F
ER Depr.	≤ 0	?	?	?	?	?	?	> 0	F

Table 1: Identification Restrictions
'S' means *slow* and 'F' means *fast*

Identified Structural Shocks

Monetary Policy Shock: A contractionary monetary policy shock considers an hike in the interbank rate, together with a decrease in output and inflation (the traditional real interest rate channel), as well as in the money aggregate in domestic currency (liquidity effect) and a decrease in the exchange rate depreciation, which is related with the uncovered interest rate parity (UIP). There is no significant effect of on interest rate spreads. We observe also a decline in cash and credit YoY growth in soles. Finally, given the higher interest rates in soles, also observe a rise in credit dollars YoY growth. Results are also in line with the empirical literature for the case of Peru (see e.g. Castillo *et al.* (2011), Pérez-Forero and Vega (2014), Aguirre *et al.* (2023), among others).

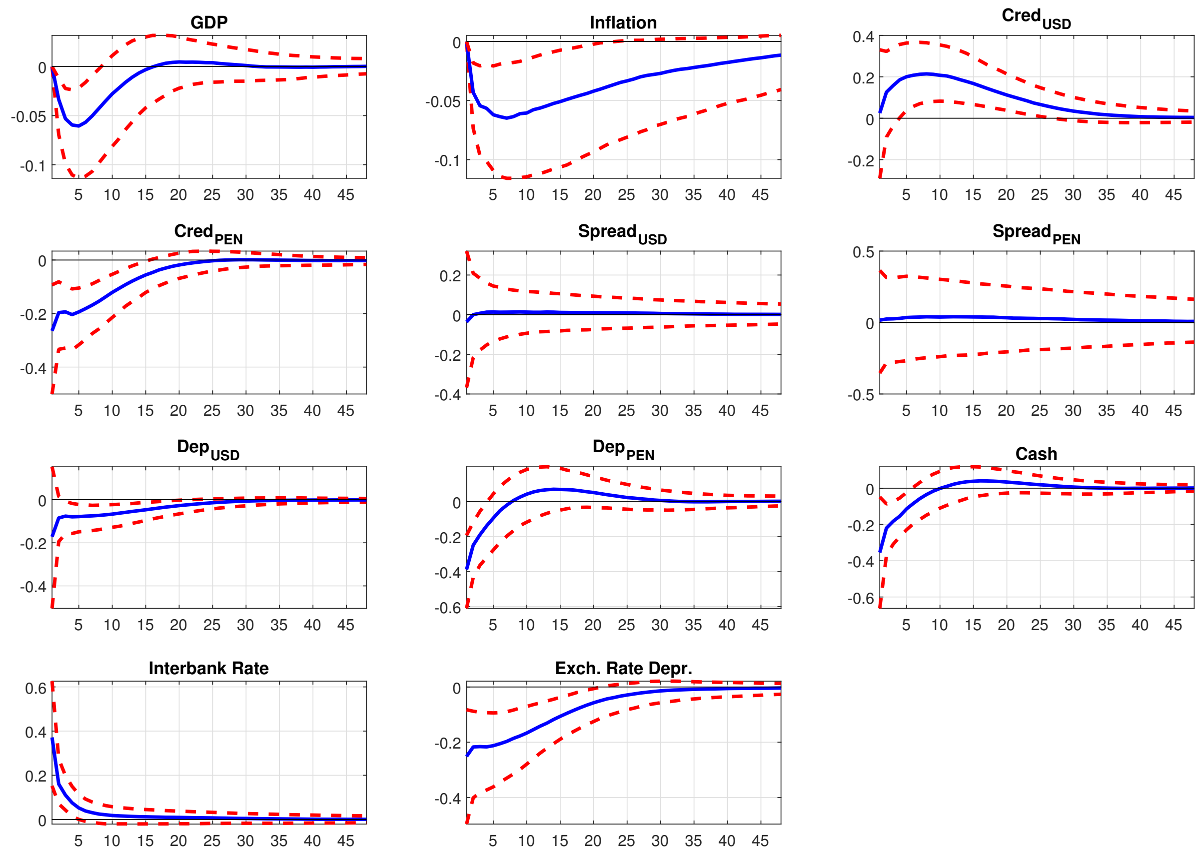


Figure 8: Monetary Policy Shock - Median value and 68% C.I.

Aggregate Demand Shock: A positive demand shock (which is in general associated with a fiscal policy expansion) considers an impulse in GDP growth, and given the demand pressures it also delivers an increase in the inflation rate. The latter also triggers a systematic response of the Central Bank by increasing the interest rate (Taylor Rule effect). Since this an impulse in domestic currency, we impose that that it has a negative effect in the Credit in Foreign Currency. The demand impulse also produces a rise in Cash, which includes the possible transfers from the government to households, as well as an acceleration of the YOY Credit growth in soles. The last two effects fit with the demand impulse provided by the government during the Covid-19 pandemic episode. In line with the macroeconomic literature, demand shocks are part of the main determinants of inflation and economic activity, and our contribution is to document the presence of this type of shocks in Peruvian data.

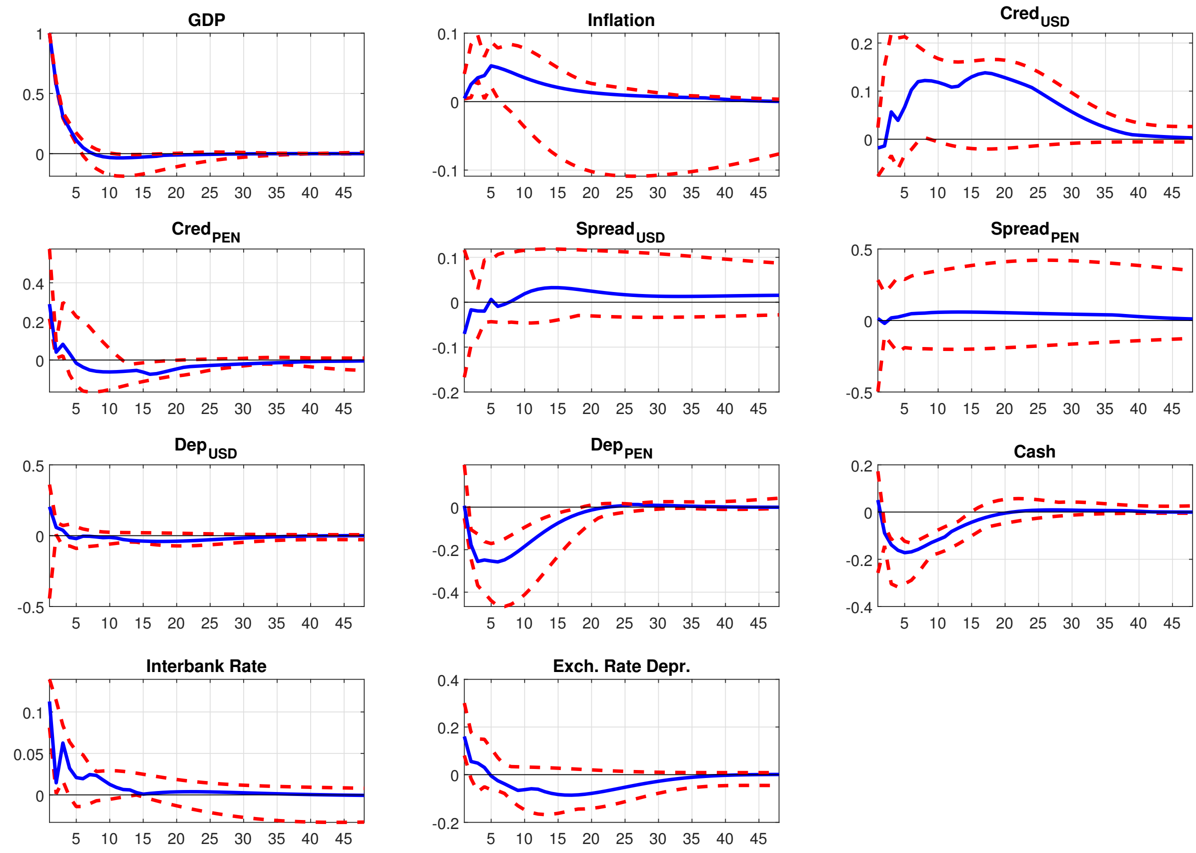


Figure 9: Aggregate Demand Shock - Median value and 68% C.I.

Aggregate Supply Shock: A negative supply shock considers an increase in headline inflation, together with a fall in output, representing the typical tradeoff or Phillips curve effect, which also triggers the systematic response of the Central Bank by increasing the interest rate (Taylor Rule effect). One of the contributions of this paper is the documentation of these supply shocks for the Peruvian economy, where we identify that the empirical literature is fairly scant about this topic. We also document that the identified macroeconomic shock does not produce any significant effect in financial variables such as credit, deposits and interest rate spreads.

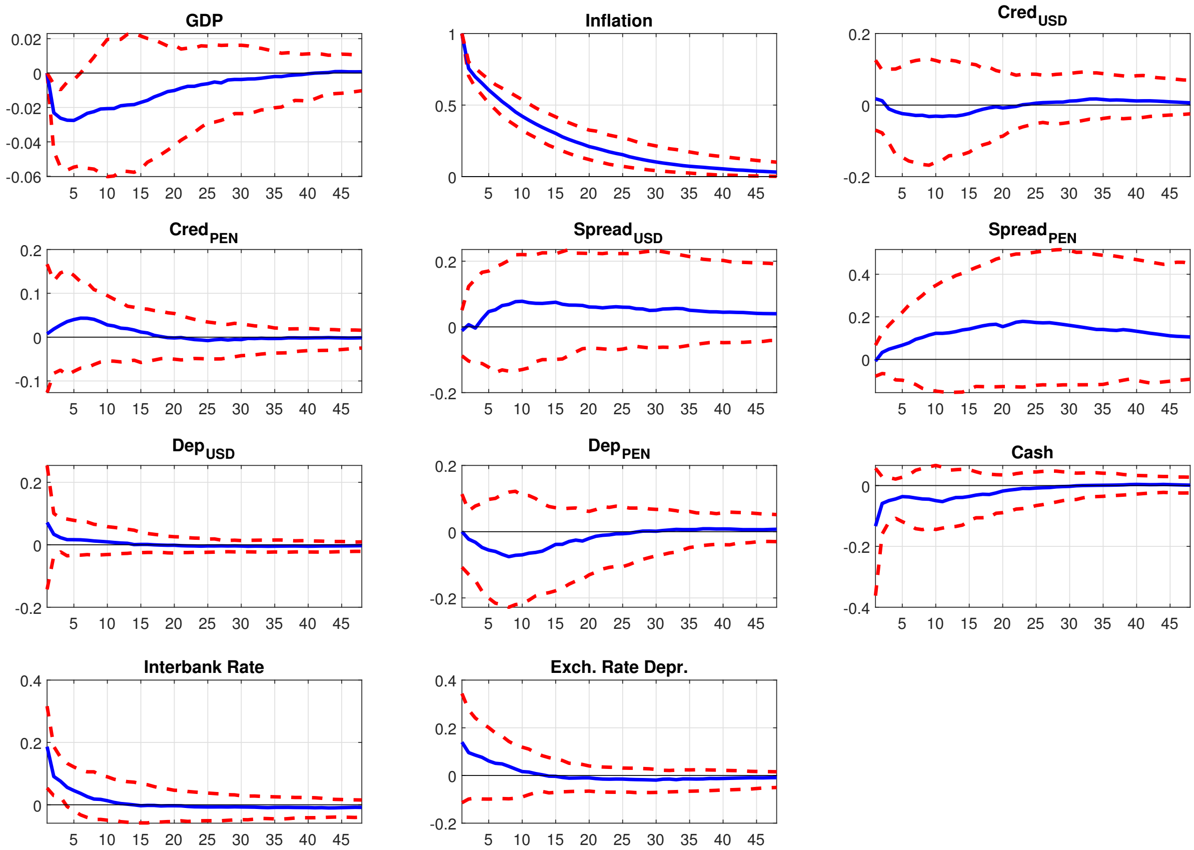


Figure 10: Aggregate Supply Shock - Median value and 68% C.I.

Credit Supply Shock (PEN): A positive credit supply shock resembles aggregate supply one, in the sense that it delivers a negative relationship between prices and quantities. In this case, we have an increase in credit in soles (PEN), and a decrease in the interest rate spread between lending and deposit rate. Following Büyükbaşaran *et al.* (2022), we also impose an increase in the headline inflation. The identified shocks were one of the main determinants of the credit impulse during the Covid-19 pandemic episode (see subsection), and also during the de-dollarization program. We impose similar restrictions for credit demand shocks in USD (see appendix B).

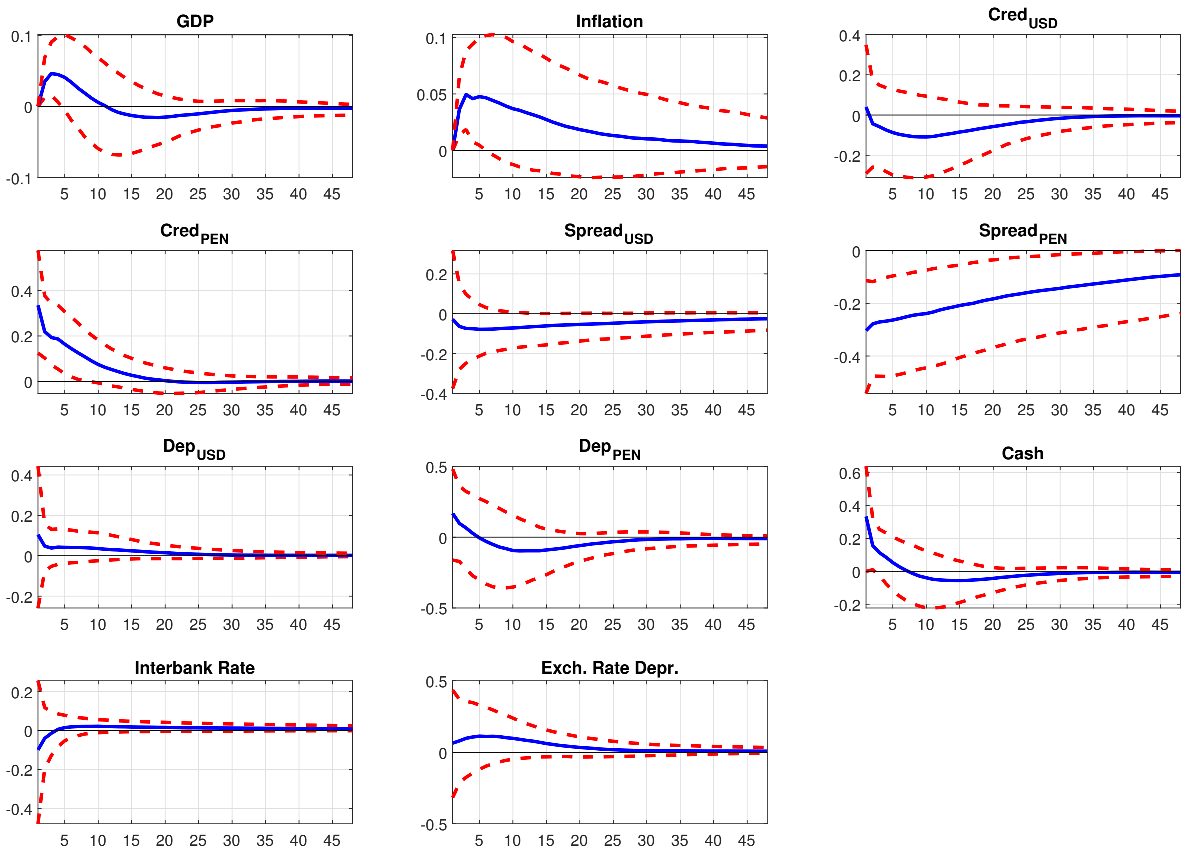


Figure 11: Credit Supply Shock (PEN) - Median value and 68% C.I.

Credit Demand Shock (PEN): A positive credit demand shock resembles aggregate demand one, in the sense that it delivers a positive relationship between prices and quantities. In this case, we have an increase in credit in soles (PEN), and an increase in the interest rate spread between lending and deposit rate. We impose similar restrictions for credit demand shocks in USD (see appendix B).

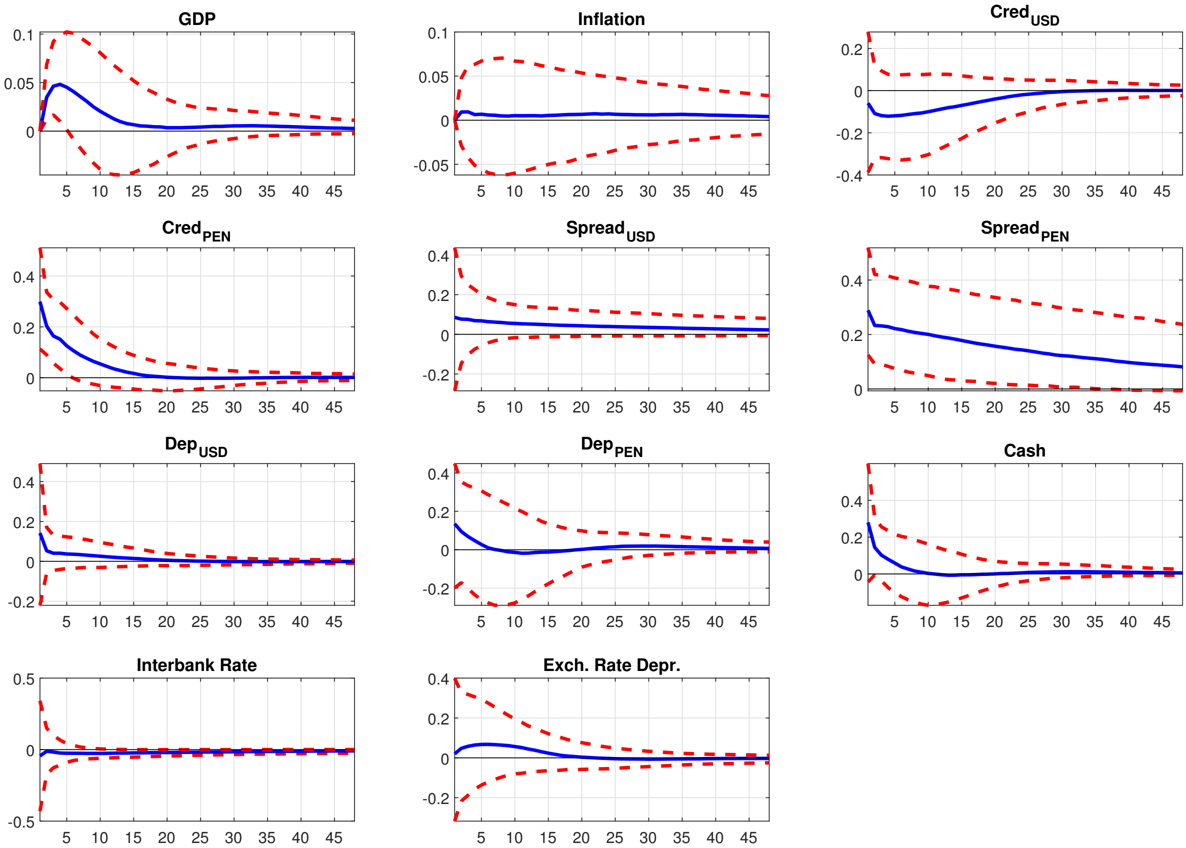


Figure 12: Credit Demand Shock (PEN) - Median value and 68% C.I.

Exchange Rate Shock: An Exchange Rate shock produces an increase in exchange rate depreciation, which delivers an increase in inflation because of the exchange rate pass-through, and because of the latter it ultimately triggers a systematic response of the Central Bank by increasing the interest rate (Taylor Rule effect). Evidence for the exchange rate shocks in Peru can be found in Castillo *et al.* (2011). In addition, evidence of the exchange rate pass-through to inflation in Peru can be found in Pérez and Vega (2015), Winkelried (2012), and Winkelried (2003).

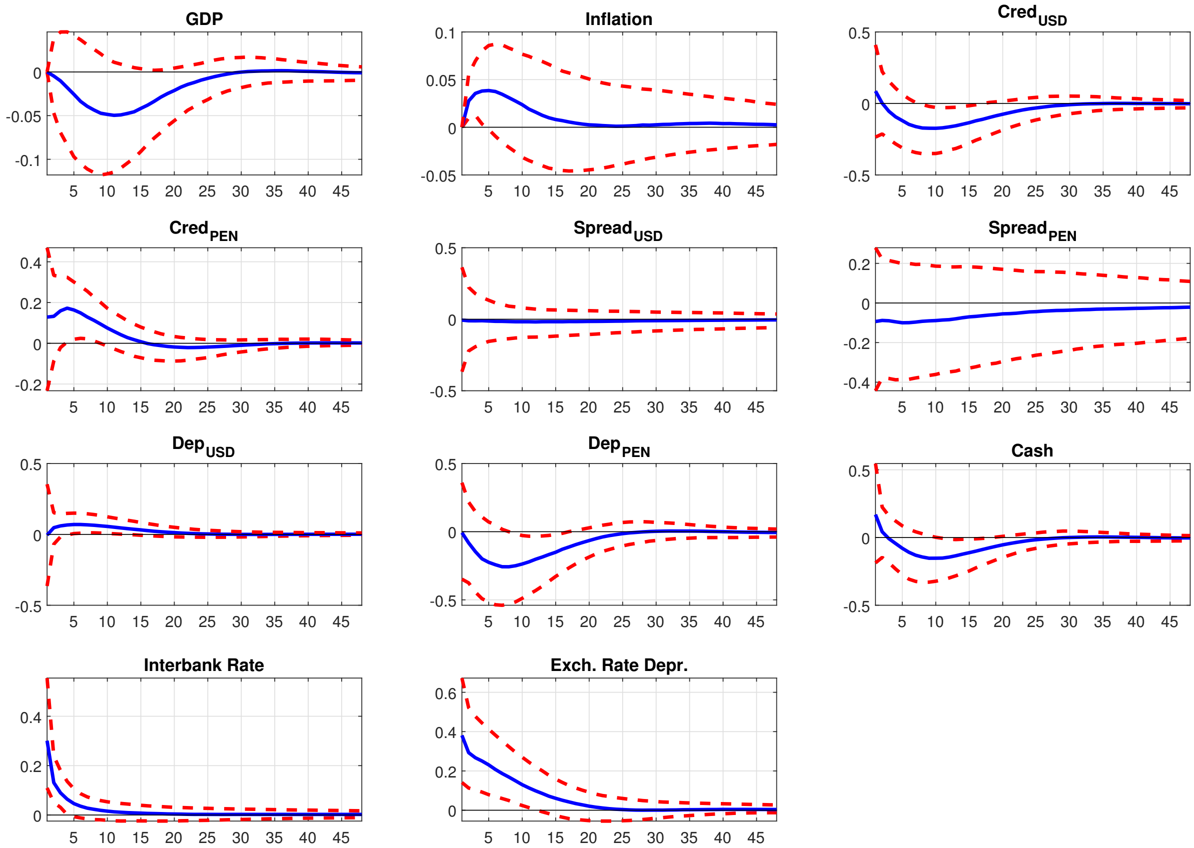


Figure 13: Exchange Rate Shock - Median value and 68% C.I.

3.4 Historical Decomposition of Aggregate Credit

One of the most interesting outputs from a SVAR system is the Historical Decomposition. That is, we can explain the history of variable of interest included in the VAR model as a function of structural shocks realizations. As a result, variable fluctuations over time have a narrative that is accompanied by the shocks' contribution at each point $t = p+1, \ldots, T$. In our particular case, recall the system (1) expressed in its structural form:

$$y_t - \tau_t = \sum_{k=1}^{p} B_k \left(y_{t-k} - \tau_{t-k} \right) + A^{-1} \Lambda_t^{\frac{1}{2}} \varepsilon_t$$

where matrices A and Λ_t are defined in subsection 2.1. We first define $\tilde{y}_t = y_t - \tau_t$, so that the variables are demeaned at each point $t = p+1, \ldots, T$, and also the matrix $C_t = A^{-1} \Lambda_t^{\frac{1}{2}}$, which can be partitioned in columns c_i, so that:

$$\tilde{y}_t = B_1 \tilde{y}_{t-1} + B_2 \tilde{y}_{t-2} + \cdots + B_p \tilde{y}_{t-p} + \begin{bmatrix} c_{1,t} & c_{2,t} & \cdots & c_{N,t} \end{bmatrix} \varepsilon_t$$

Re-expressing the system in its companion form, we get

$$\tilde{\mathbf{Z}}_t = \tilde{\mathbf{B}} \tilde{\mathbf{Z}}_{t-1} + \tilde{\mathbf{H}} C_t \varepsilon_t \tag{12}$$

where

$$\tilde{\mathbf{Z}}_t = \begin{bmatrix} \tilde{y}_t \\ \tilde{y}_{t-1} \\ \vdots \\ \tilde{y}_{t-p+1} \end{bmatrix}; \tilde{\mathbf{B}} = \begin{bmatrix} B_1 & B_2 & \cdots & B_{p-1} & B_p \\ I_N & \mathbf{0} & \cdots & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & I_N & \cdots & \mathbf{0} & \mathbf{0} \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ \mathbf{0} & \mathbf{0} & \cdots & I_N & \mathbf{0} \end{bmatrix}; \tilde{\mathbf{H}} = \begin{bmatrix} I_N \\ \mathbf{0} \end{bmatrix}$$

Equation (12) can be iterated backwards, so that it can be expressed as a function of its initial condition $\tilde{\mathbf{Z}}_0$[10]:

[10]See details in Wong (2017).

$$\tilde{\mathbf{Z}}_t = \tilde{\mathbf{B}}^t \tilde{\mathbf{Z}}_0 + \sum_{k=0}^{t-1} \tilde{\mathbf{B}}^k \tilde{\mathbf{H}} C_{t-k} \varepsilon_{t-k}$$

The, using the partitioned matrix C_t in columns $C_t = \begin{bmatrix} c_{1,t} & c_{2,t} & \cdots & c_{N,t} \end{bmatrix}$ we get

$$\tilde{\mathbf{Z}}_t = \tilde{\mathbf{B}}^t \tilde{\mathbf{Z}}_0 + \sum_{k=0}^{t-1} \tilde{\mathbf{B}}^k \tilde{\mathbf{H}} \begin{bmatrix} c_{1,t-k} & c_{2,t-k} & \cdots & c_{N,t-k} \end{bmatrix} \varepsilon_{t-k}$$

Using the fact that $C_{t-k}\varepsilon_{t-k} = \sum_{i=1}^{N} c_{i,t-k} \odot \varepsilon_{t-k}$, we can decompose the vector $\tilde{\mathbf{Z}}_t$ as the sum of N contributions plus the initial condition $\tilde{\mathbf{Z}}_0$, thus

$$\tilde{\mathbf{Z}}_t = \tilde{\mathbf{B}}^t \tilde{\mathbf{Z}}_0 + \sum_{i=1}^{N} \sum_{k=0}^{t-1} \tilde{\mathbf{B}}^k \tilde{\mathbf{H}} c_{i,t-k} \odot \varepsilon_{t-k} \tag{13}$$

Recall that $\tilde{\mathbf{Z}}_t$ contains the time varying means vector τ_t. We define the selection matrix $\mathbf{J}$ such that $y_t - \tau_t = \mathbf{J}\tilde{\mathbf{Z}}_t$. As a result we get the historical decomposition of y_t as a function of the time varying mean, the initial condition and the sum of N shock contributions.

$$y_t = \underbrace{\tau_t}_{TV-Mean} + \underbrace{\mathbf{J}\tilde{\mathbf{B}}^t \tilde{\mathbf{Z}}_0}_{Initial} + \sum_{i=1}^{N} \underbrace{\left[\sum_{k=0}^{t-1} \mathbf{J}\tilde{\mathbf{B}}^k \tilde{\mathbf{H}} c_{i,t-k} \odot \varepsilon_{t-k} \right]}_{Shocks} \tag{14}$$

The latter equation (14) can be interpreted as follows: Each macroeconomic variable included in vector y_t can be decomposed as the sum of i) a Time-Varying Mean, ii) a Initial condition, and iii) The sum of structural shocks contributions. We now proceed to show the resulting historical decomposition for aggregate credit in soles in Figure 14 and in USD in Figure 15. In first place, a large fraction of credit growth is explained by the time varying mean vector τ_t, i.e. the part associated with the trend growth of y_t. However, the cyclical component of credit can be decomposed in contributions associated with the identified structural shocks. In this regard, although we can observe the contribution of monetary policy and other structural shocks for the full sample (2002-2024), we focus our attention in two relevant episodes for credit dynamics: i) the Covid-19 pandemic episode and the Reactiva Perú program (2020-2021), and ii) The De-dollarization program (2014-2018).

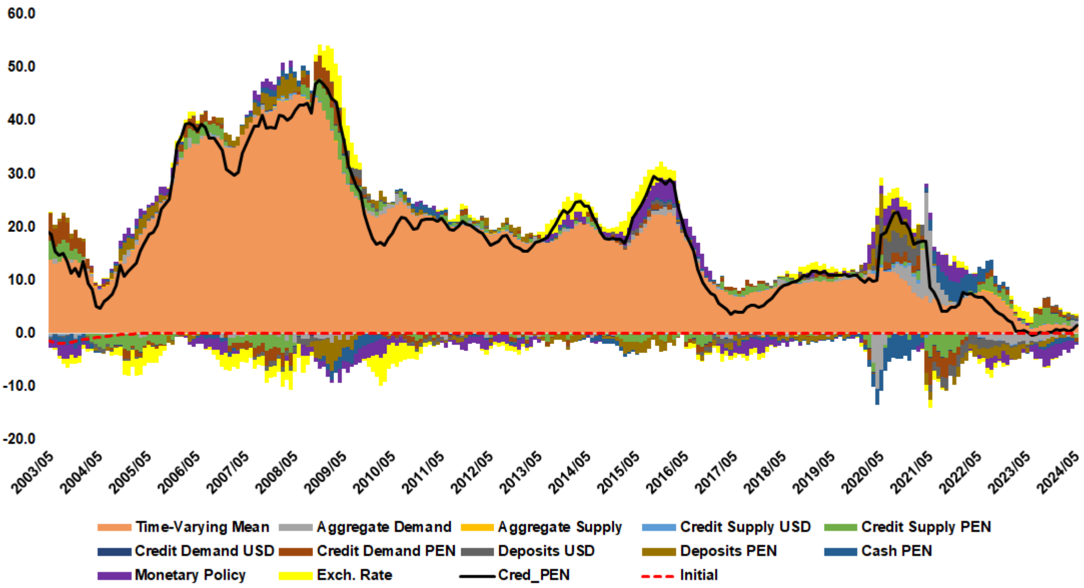


Figure 14: HD: Credit to the Private Sector - PEN (2002-2024)

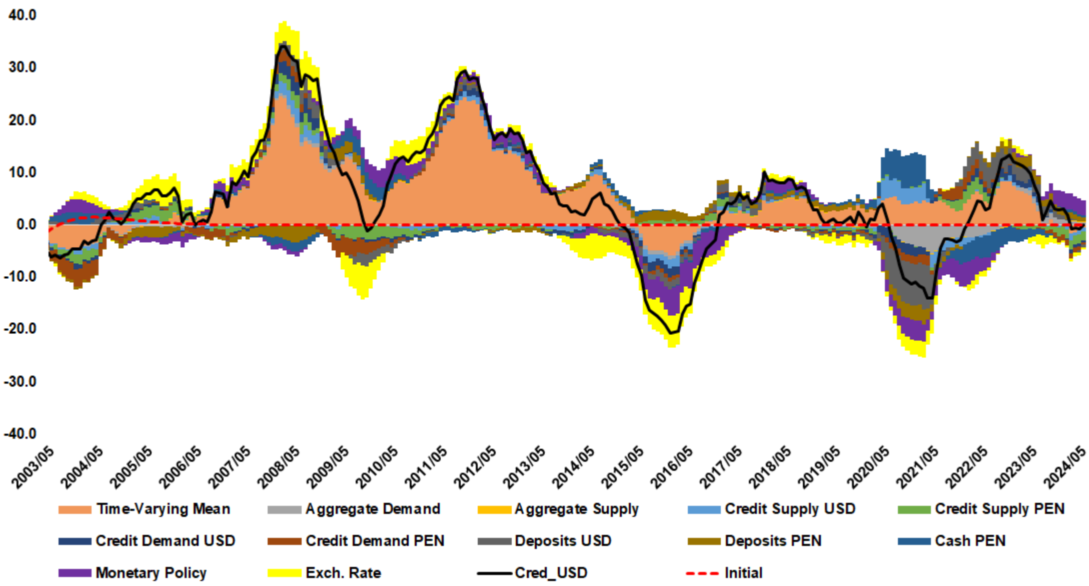


Figure 15: HD: Credit to the Private Sector - USD (2002-2024)

The Covid-19 episode and the Reactiva Perú program

The Reactiva Perú program was implemented as a policy reaction given the emergency state in march-april 2020. The program consisted on the provision of Government-Guaranteed Liquidity for the Financial System, with the purpose of channelizing these resources to the economy through loans in soles (see details in Montoro (2020)). In terms of the historical decomposition of credit in soles, we can observe in Figure 16: i) a monetary policy impulse (mainly through the interest rate cut and the liquidity provision), ii) a credit supply impulse in soles reflecting the effect of the program, iii) a negative effect from the aggregate demand shocks (mainly related with the Covid-19 lockdown).

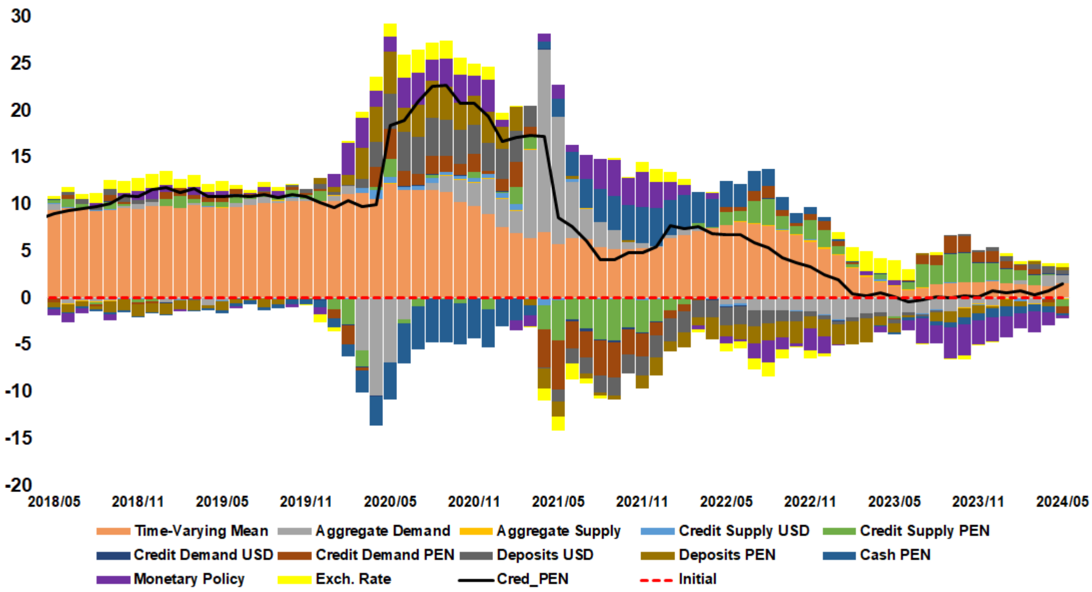


Figure 16: HD: Credit to the Private Sector - PEN (2018-2024)

A crucial question in this context is: **what would have happened without this program?** Given the identified structural factors, we present the counterfactual scenario that considers the case when we eliminate the effect of these shocks, and the resulting path of credit in soles is depicted in Figure 17. We observe a negative growth of credit at the beginning of the Covid-19 pandemic episode, which would have been associated with a credit crunch and a break in the payments chain, resulting in a harmful and serious effect on the Peruvian economy.

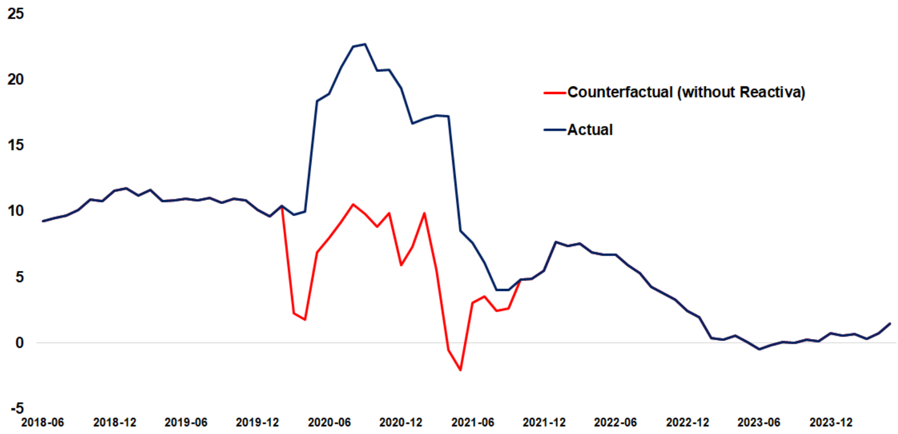


Figure 17: Counterfactual: Credit to the Private Sector - PEN (2018-2024)

The de-Dollarization program

Turning to the de-dollarization program (2014-2018), we observe in Figure 18 that the main acceleration of credit in soles in explained by monetary policy shocks, credit supply shocks in soles as well as exchange rate shocks, which in this case correspond to the portfolio ones. The mentioned program was mainly associated with a long term liquidity provision in domestic currency (soles), as well as the introduction of additional reserve requirements in foreign currency conditioned on a credit level target for the end of each year (2015, 2016, and 2017).

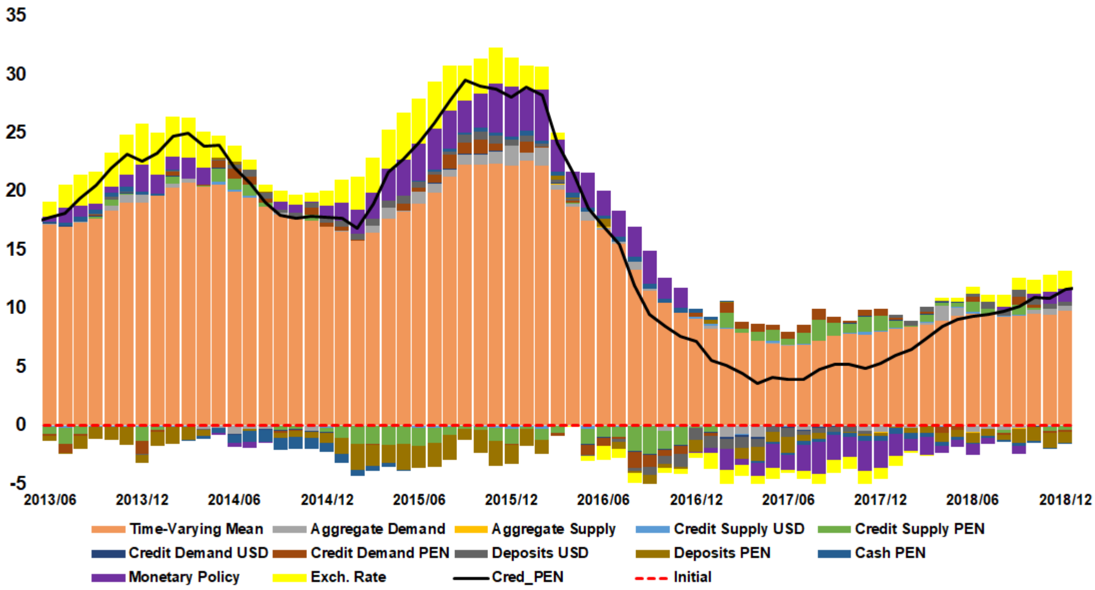


Figure 18: HD: Credit to the Private Sector - PEN (2013-2018)

Conversely, we observe in Figure 19 for the same period a large fall in foreign currency credit, and the historical decomposition validates the program indicating that a large fraction of this fall was associated with monetary policy shocks, liquidity provision in soles as well as exchange rate portfolio shocks.

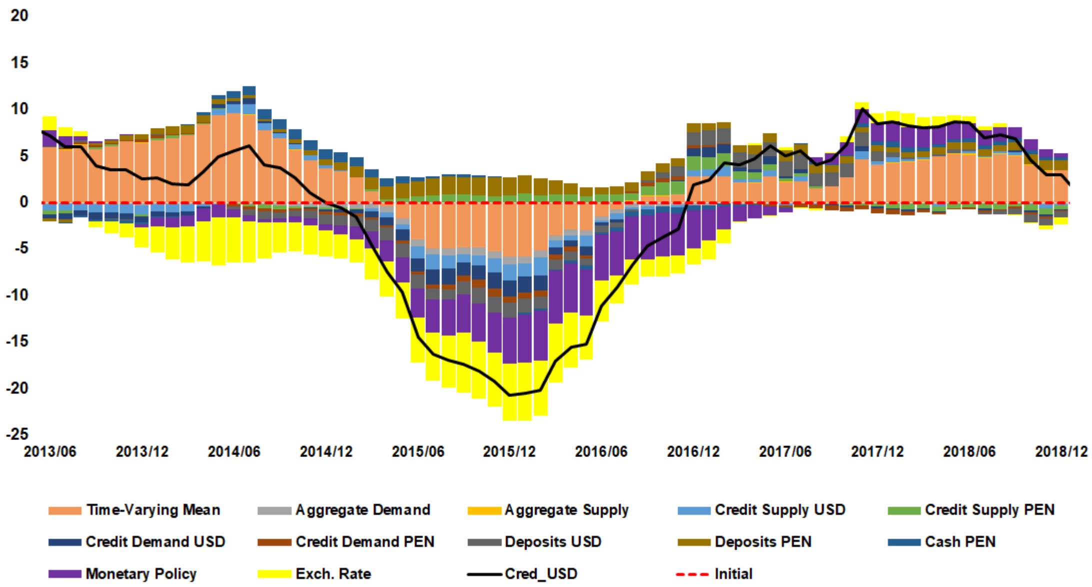


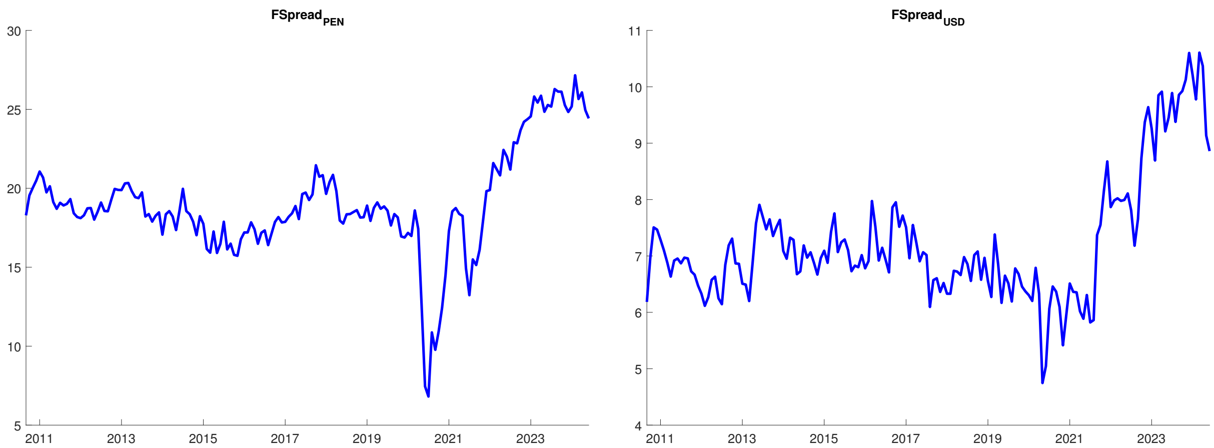
Figure 19: HD: Credit to the Private Sector - USD (2013-2018)

4 Robustness checks - Alternative specifications

In this section we consider two alternative models with different variables for measuring interest rate spreads. More specifically, in the original model (M1) we use lending and deposit rates for the total stock of credits. However, interest rates associated with total balances might be very inertial, since they include the whole set of credits without filtering the fact that there exists a fraction with potential problems, etc. Therefore, we specify two alternative models replacing these spreads with alternative variables. In first place, we employ flow interest rates, i.e. the ones associated with 'new' credits and deposits with a rolling window of 30 days calendar, and we compute the spread for both currencies (see Figure 20). In second place, we employ estimated financial conditions indexes (FCI) for the Peruvian economy[11], both in domestic and foreign currency (see Figure 21).

Figure 20: **Peru: Flow Interest Rate Lending-Deposit Spreads (2010-2024)**

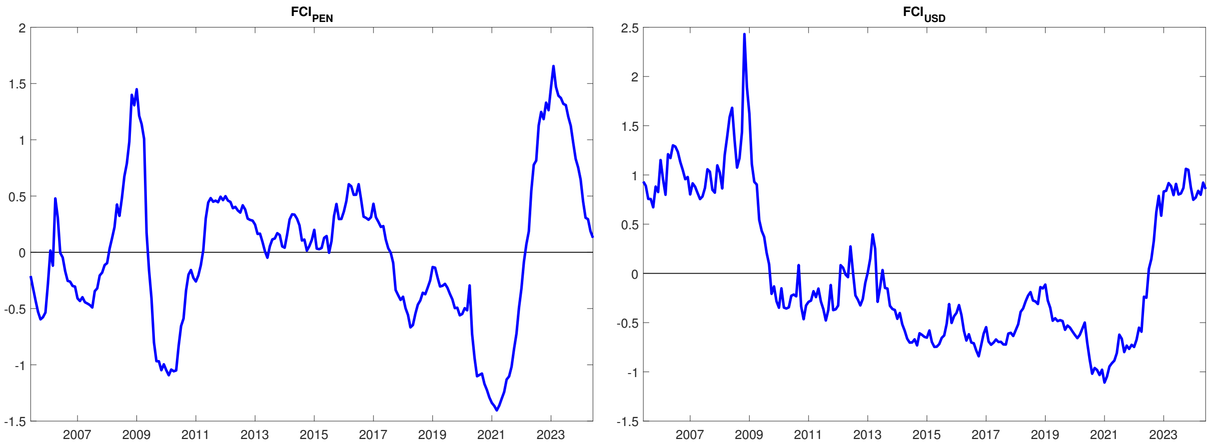
(a) Soles (PEN) (b) US$ (USD)



[11]See details in Pérez Forero (2024).

Figure 21: **Peru: Financial Conditions Indexes (2005-2024)**

(a) Soles (PEN) (b) US$ (USD)

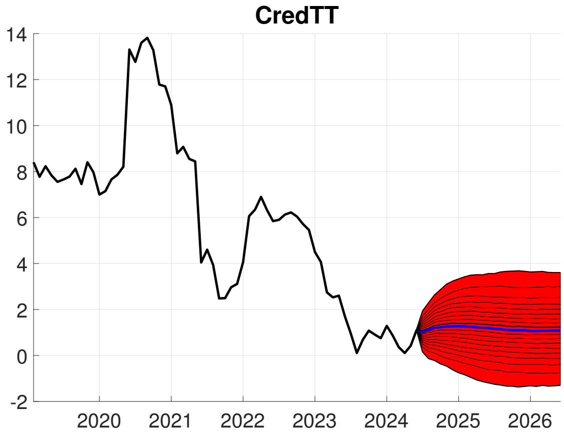


As a result, we consider the following alternative specifications:

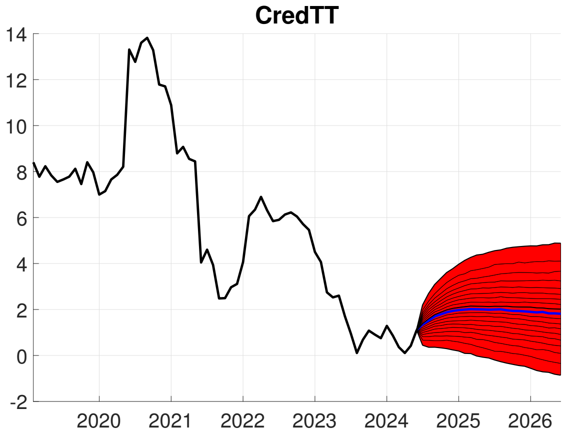
- **Model 2 (M2)**: Flow interest rates, i.e. the average lending and deposit rates for the last 30 days, for both domestic and foreign currency.
- **Model 3 (M3)**: New Financial conditions indexes, for both domestic and foreign currency.

We estimate the two additional models up to May 2024 and perform the forecast for $\overline{H} = 24$, i.e. two years. Results for total aggregate credit are depicted in figure 22. We do not observe a significant shift in posterior estimates relative to model 1 (M1), although Model 3 (M3) suggests a higher median value for credit growth in the medium run[12]. All in all, our results are robust to changes in the financial variables considered in the the information set.

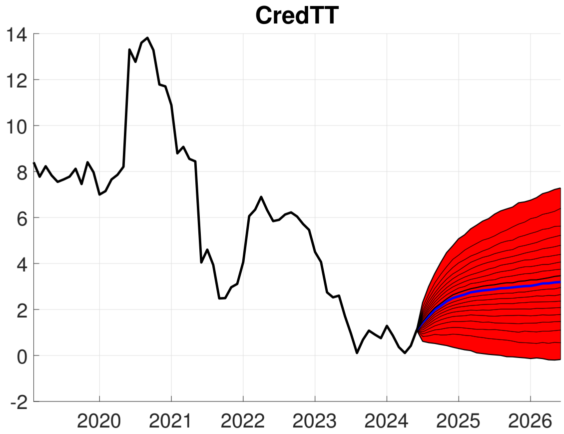
[12]Results for other variables are available upon request.



(a) M1



(b) M2



(c) M3

Figure 22: Total Credit YoY Growth Forecast - Fan charts of 95% of probability

5 Concluding Remarks

We have estimated a Time Varying Mean BVAR model with Stochastic Volatility for the Peruvian economy. We present forecast scenarios for aggregate credit, deposits and cash. We have also identified credit demand and supply shocks in domestic and foreign currency, as well as other tradition macroeconomic shocks. The historical decomposition shows that the last deceleration in aggregate credit in domestic currency is explained by negative exchange rate shocks, negative aggregate demand and supply shocks, and also because of the monetary tightening. The historical decomposition also shows that the last deceleration in aggregate credit in foreign currency is explained by negative credit supply shocks in both currencies. All in all, we apply a flexible framework for forecasting Peruvian monetary aggregates, and the latter should be useful as a starting point for a Financial Programming exercise.

A Time Varying Mean-BVAR-SV details

A.1 The Forecasting Algorithm

This section describes the algorithm for computing the posterior distribution of forecasts. Set first $\overline{\mathbf{S}} = 2,000$ number of draws, a given horizon $\overline{H}$ and $L = 200$.

1. Draw Θ from the posterior distribution $p\left(\Theta \mid y^T, z^T\right)$.
2. Consider y_T and $\{\tau_T, ln\left(\Lambda_T\right), ln\left(V_T\right), ln\left(G_T\right)\}$ as the initial point for computing forecasts.
3. For each horizon point in time $h = 1, \ldots, \overline{H}$ do:
   - For each l in $l = 1, \ldots, L$ do:
     - Draw the vectors $\{\varepsilon^l_{T+h}, \eta^l_{T+h}, g^l_{T+h}\}$ from $N\left(0, \varrho\right)$, where $\varrho \in \{\phi_H, \phi_V, \phi_G\}$.
     - Forecast Volatilities $\{ln\left(\Lambda^l_{T+h}\right), ln\left(V^l_{T+h}\right), ln\left(G^l_{T+h}\right)\}$ using equation (4)
     - Forecast τ^l_{T+h} using equation (2)
     - Forecast $\{y^l_{T+h}, z^l_{T+h}\}$ using equations (1) – (3)
   - Take averages of $\{\tau^l_{T+h}, y^l_{T+h}, z^l_{T+h}\}$ over $l = 1, \ldots, L$.
4. If $s < \overline{\mathbf{S}}$, return to Step 1, otherwise stop.

A.2 The Algorithm for imposing Zero and Sign Restrictions

1. Set first $\overline{\mathbf{S}} = 2,000$ number of draws.
2. Draw (B, A) from the posterior distribution $p\left(\Theta \mid, y^T, z^T\right)$. Then we compute normalized impulse responses with respect to the time-varying volatility as follows:

$$IRF\left(B, A, h\right) = JF^h J' A^{-1}, h = 0, 1, \ldots, H$$

   where F is the companion form matrix associated with B and J is a matrix that selects the upper-left block.

3. Draw $\mathbf{X} \sim N(0, I_{K-k})$ and get $\mathbf{Q}$ such that $\mathbf{QR} = \mathbf{X}$, i.e. an orthogonal matrix $\mathbf{Q}$ that satisfies the QR decomposition of $\mathbf{X}$. The random matrix $\mathbf{Q}$ has the uniform distribution with respect to the Haar measure on $O(K-k)$.

4. Construct the matrix:
$$\overline{\mathbf{Q}} = \begin{bmatrix} \mathbf{I}_k & \mathbf{0}_{(k \times K-k)} \\ \mathbf{0}_{(K-k \times k)} & \mathbf{Q} \end{bmatrix}$$
That is, a subset of $k < K$ variables in $\left(y^T\right)$ are going to be *slow* (S) and therefore they do not rotate. This is how we impose zero restrictions in this case. In our case we set $k = 5$ variables, i.e. slow variables are Inflation, GDP, and aggregate credit in both currencies.

5. Compute the matrices $\overline{\mathbf{A}}_0 = (A)\,\overline{\mathbf{Q}}$, then compute the impulse responses for $h = 0, 2, \ldots, H$.

6. If sign restrictions are satisfied for a horizon $\overline{h} < H$, keep the draw and set $s = s + 1$. If not, discard the draw.

7. If $s < \overline{\mathbf{S}}$, return to Step 2, otherwise stop.

B Additional figures

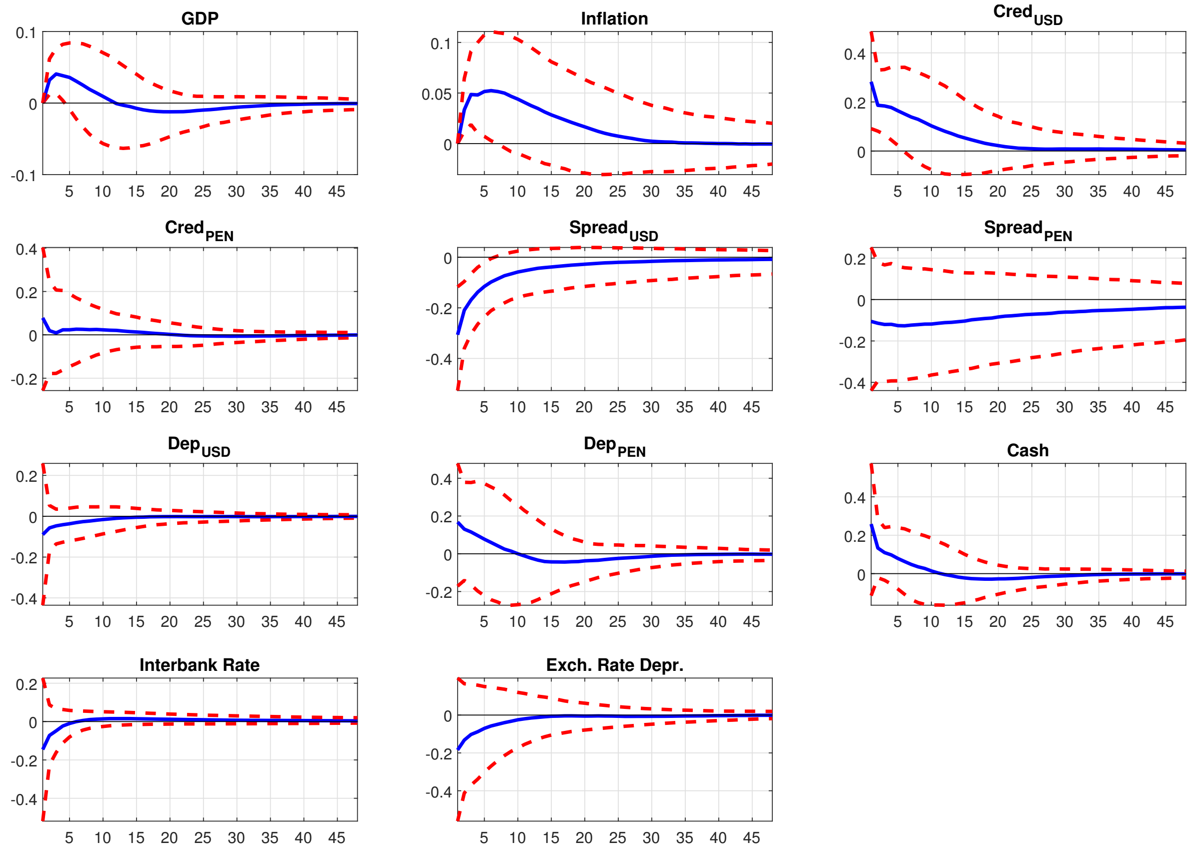


Figure B.23: Credit Supply Shock (USD) - Median value and 68% C.I.

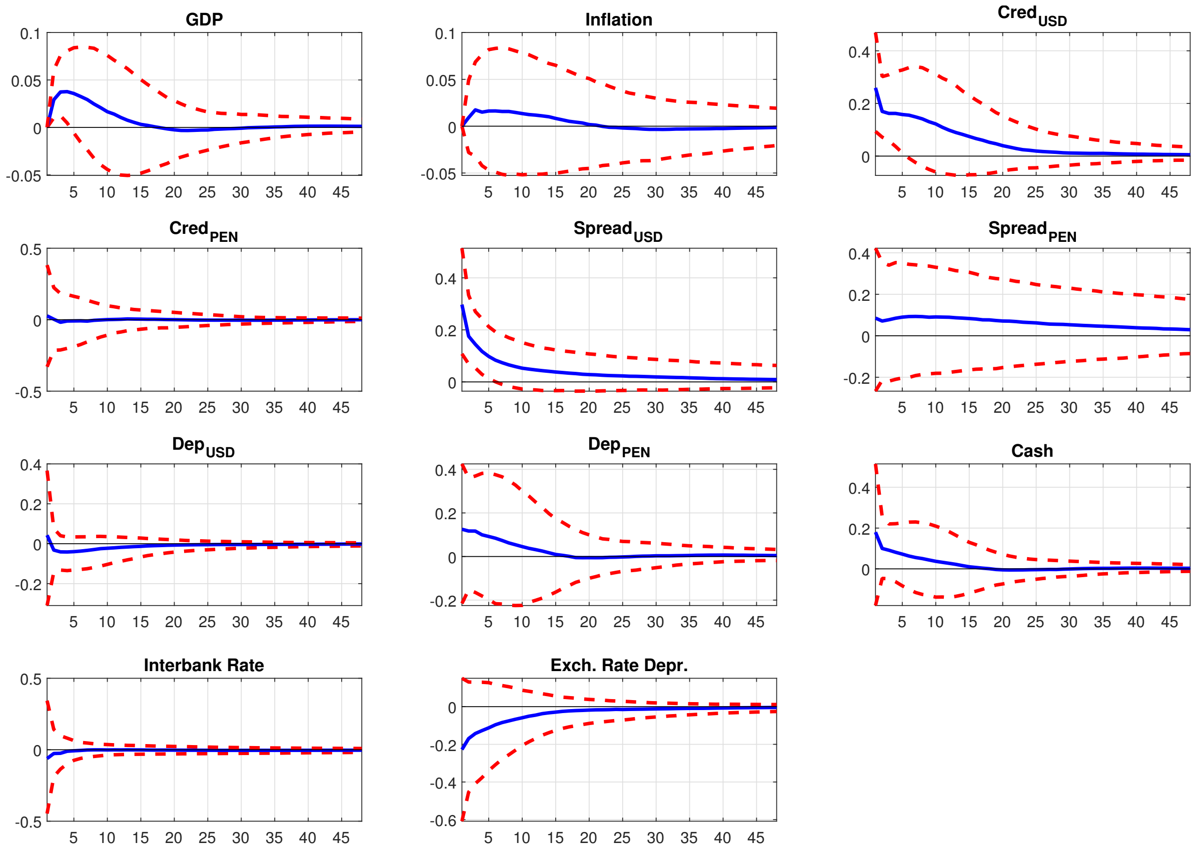
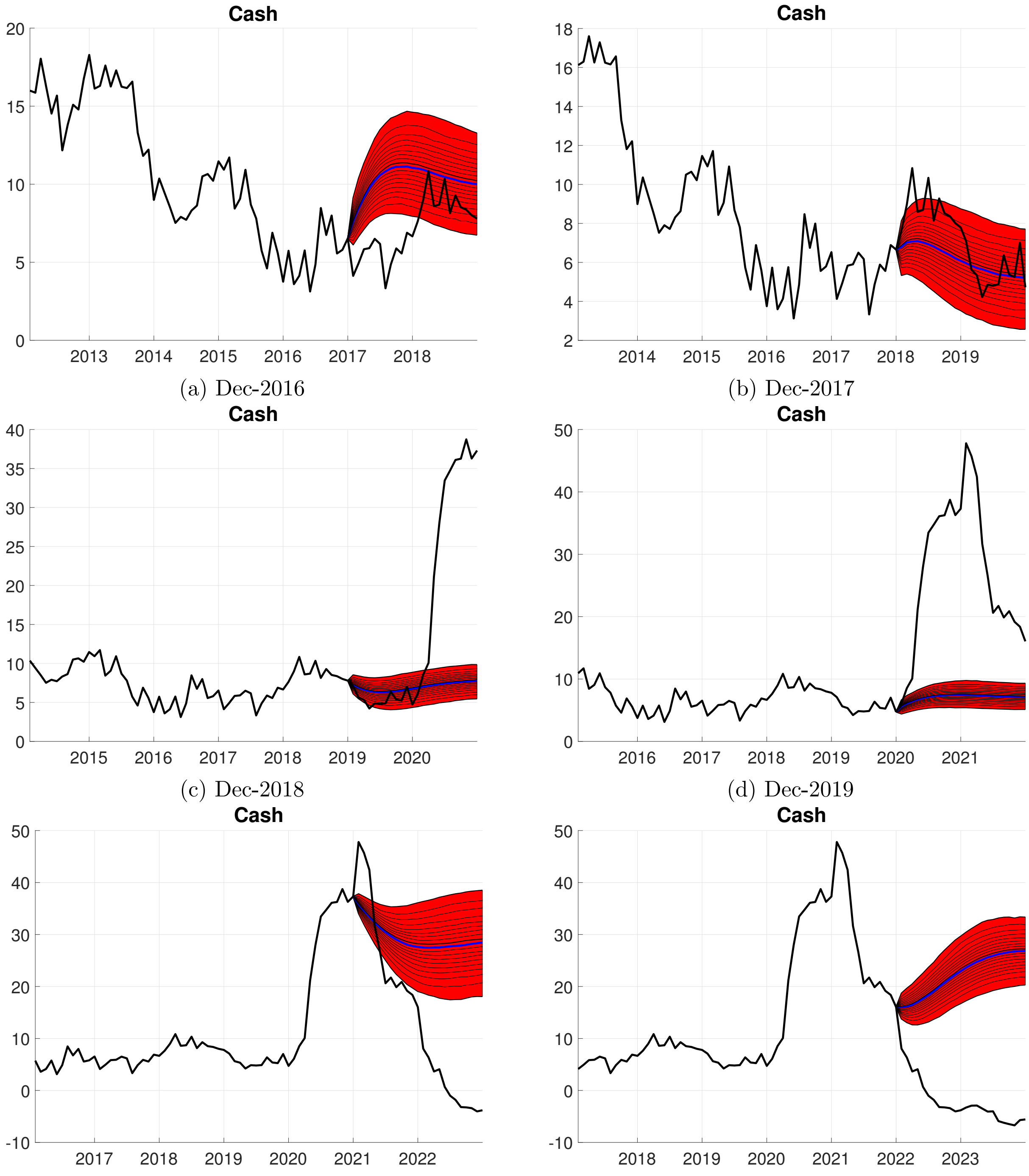


Figure B.24: Credit Demand Shock (USD) - Median value and 68% C.I.

Predictive Power Evaluation for Other Money Aggregates in Model 1



(a) Dec-2016
(b) Dec-2017
(c) Dec-2018
(d) Dec-2019
(e) Dec-2020
(f) Dec-2021

Figure B.25: Cash YoY Growth Forecast - Fan charts of 95% of probability

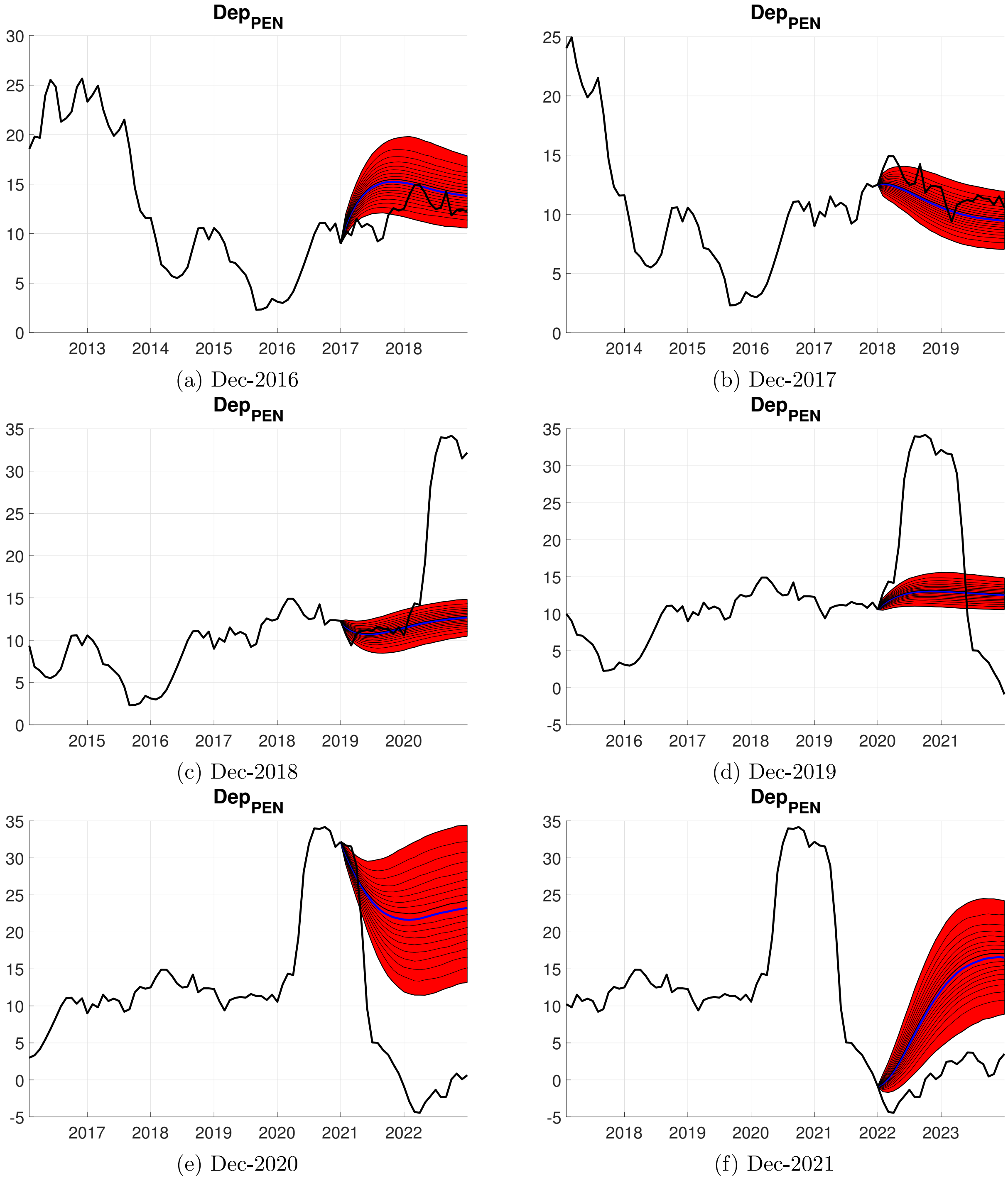
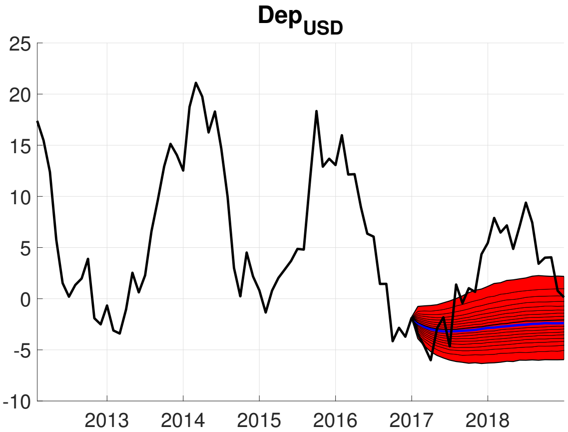
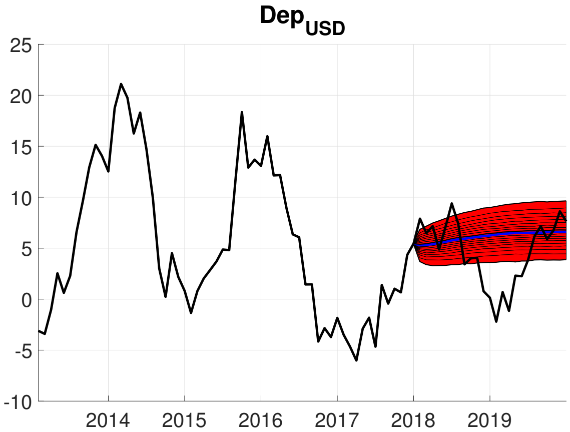


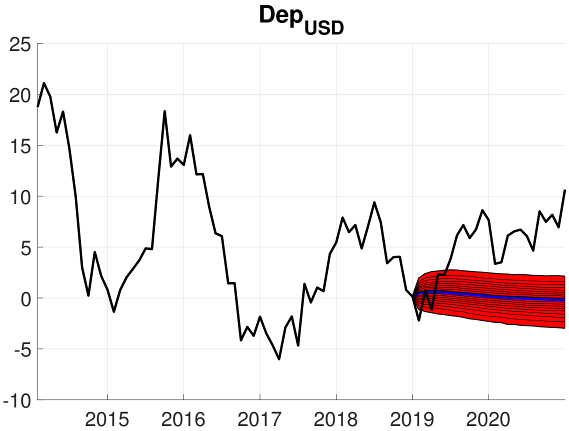
Figure B.26: Deposits PEN YoY Growth Forecast - Fan charts of 95% of probability



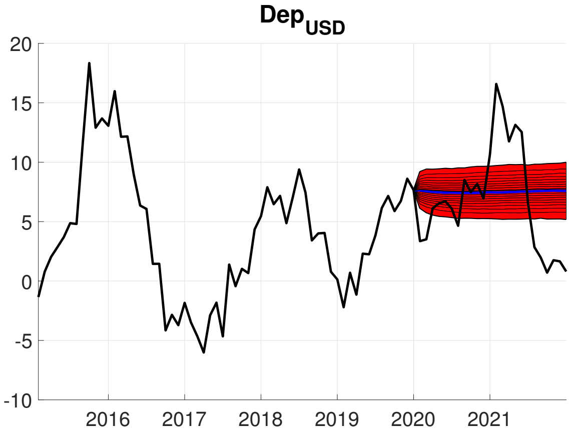
(a) Dec-2016



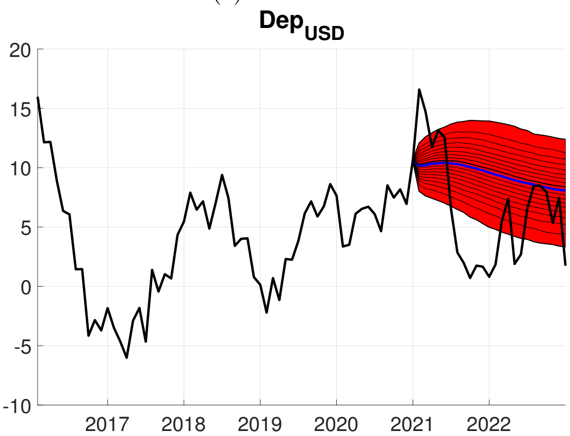
(b) Dec-2017



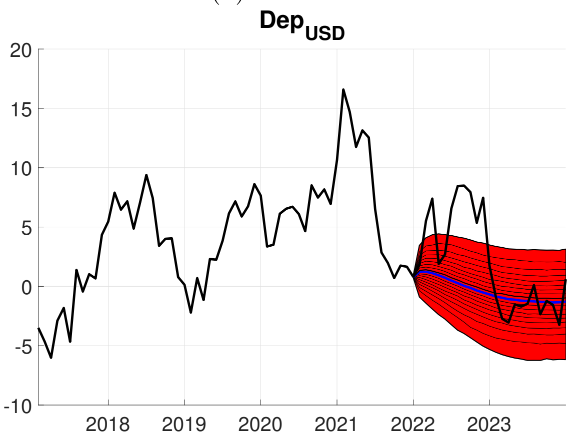
(c) Dec-2018



(d) Dec-2019



(e) Dec-2020



(f) Dec-2021

Figure B.27: Deposits USD YoY Growth Forecast - Fan charts of 95% of probability

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