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Robust Estimation of Credit Shocks in Peru during the COVID-19 Crisis

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Abstract: The Covid-19 pandemic introduced an unprecedented disruption in macroeconomic activity while credit continued to expand in several economies due to large policy interventions aimed at preserving financial intermediation. In Peru, this episode represented a clear deviation from the historical relationship between credit growth and economic activity. This paper studies the transmission of credit supply and credit demand shocks using a Bayesian structural VAR estimated with monthly macro-financial data from 2010 to 2024. To account for the extreme volatility observed during the pandemic, the identification combines sign and zero restrictions with information from higher-order moments and heteroskedasticity. The results indicate that, conditional on the maintained identifying assumptions, credit supply shocks are associated with stronger responses of economic activity during and after the pandemic than in the pre-pandemic period, while credit demand shocks display weaker and less persistent responses. These findings suggest that credit conditions became a more important driver of macroeconomic fluctuations during episodes of heightened uncertainty, although the framework does not separately identify policy-induced credit shocks.

Keywords: Credit shocks, robust Bayesian inference, SVAR, sign restrictions, zero restrictions, Covid-19.

JEL Classification: C32, E51, G01.

1. Introduction

The Covid-19 pandemic generated one of the largest disruptions to economic activity in recent decades. In many economies, output collapsed abruptly while governments and central banks implemented extraordinary policies aimed at stabilizing financial conditions and preserving the flow of credit to firms and households. As a result, credit markets experienced unusually large fluctuations in lending volumes, spreads, and financial conditions. In Peru, the pandemic period was characterized by a particularly striking combination of a sharp contraction in economic activity and continued expansion in credit aggregates, largely supported by large credit guarantee programs such as Reactiva Perú. This episode represents a clear deviation from the historical relationship between credit growth and economic activity and raises an important macro-financial question: did the transmission of credit shocks change during the pandemic period?

Distinguishing between credit supply and credit demand shocks has long been a central challenge in macro-financial analysis. Structural vector autoregressions (SVARs) identified using sign and zero restrictions have become one of the most widely used empirical approaches for studying credit market disturbances (Barnett & Thomas, 2014; Duchi & Elbourne, 2016; Büyükbaşaran et al., 2022). These methods allow researchers to impose economically motivated restrictions on impulse responses while remaining agnostic about the exact contemporaneous structure of the economy.

However, periods characterized by extreme volatility and large macroeconomic disruptions, such as the Covid-19 pandemic, pose challenges for standard identification approaches. Macroeconomic time series during the pandemic exhibited unusually large movements, abrupt changes in volatility, and deviations from normality. These features may reduce the informational content of conventional sign restrictions by widening the set of admissible structural models and complicating inference about the transmission of structural credit shocks. In particular, the presence of large outliers and volatility clustering may weaken the ability of traditional Gaussian VAR frameworks to capture the true dynamics of macro-financial variables during crisis episodes.

This paper studies the identification and transmission of credit supply and credit demand shocks in Peru using monthly macro-financial data spanning the period from 2010 to 2024, which includes the pre-pandemic period, the pandemic shock, and the subsequent recovery. Peru provides an informative setting for studying credit dynamics in emerging markets, where bank credit plays a central role in the transmission of macroeconomic shocks and where policy interventions during the pandemic were particularly large relative to the size of the financial system.

Our empirical strategy builds on the structural VAR literature but adapts the identification framework to account for the unusual statistical properties of macro-financial data observed during the pandemic. Recent contributions have shown that higher-order moments and heteroskedasticity can provide additional identifying information for structural shocks when the standard Gaussian assumption is violated. In particular, Lenza and Primiceri (2022) emphasize the importance of explicitly modeling the temporary volatility spike associated with the pandemic, while Bobeica and Hartwig (2023) show that allowing for fat-tailed error distributions can improve parameter stability in VAR models estimated during periods of extreme economic disturbances. Similarly, Andrade et al. (2023) demonstrate that incorporating higher-moment restrictions can help shrink the identified set of structural impulse responses in sign-identified VARs.

Motivated by these developments, the empirical analysis combines three complementary sources of identification. First, we impose conventional sign and zero restrictions motivated by standard credit market mechanisms to distinguish between credit supply and credit demand disturbances. Second, we exploit information contained in higher-order moments of the data, allowing non-Gaussian features such as excess kurtosis to refine identification in set-identified SVARs. Third, we incorporate heteroskedasticity adjustments that explicitly account for the temporary surge in volatility observed at the onset of the pandemic. Together, these elements allow us to obtain impulse responses that are more robust to extreme observations and volatility patterns associated with the Covid-19 shock.

Our analysis yields three main findings. First, the estimated shocks display clear evidence of non-Gaussian features, indicating that higher-order moments contain useful information for identifying macro-financial disturbances during crisis episodes. Second, credit supply shocks have a positive and persistent effect on economic activity, with significantly stronger responses during the pandemic and post-pandemic periods compared to the pre-pandemic sample. This pattern suggests that fluctuations in credit conditions became a more important driver of macroeconomic dynamics during episodes of heightened uncertainty. Third, credit demand shocks display weaker and less persistent effects, indicating that fluctuations in credit supply conditions played a particularly important role during the pandemic period. While these results are consistent with the possibility that policy interventions aimed at sustaining credit flows strengthened the macroeconomic role of credit supply shocks, the empirical framework does not directly identify policy-induced shocks. The findings should therefore be interpreted as evidence on how the transmission of credit conditions changed during a period of extreme macroeconomic stress.

From an economic perspective, the paper provides new evidence on how the transmission of credit shocks can change during large systemic disruptions. Using the Covid-19 crisis as a natural stress episode for credit markets, we document that the macroeconomic effects of credit supply shocks became stronger and more persistent during and after the pandemic relative to the pre-pandemic period. This finding suggests that credit conditions may play a more prominent role in driving macroeconomic fluctuations when economies face extreme uncertainty and large credit-support interventions.

This paper contributes to the literature by documenting how the macroeconomic transmission of credit supply shocks changed during an extreme policy intervention episode in an emerging economy. By comparing pre-pandemic, pandemic, and post-pandemic periods within a unified empirical framework, the analysis provides new evidence on how the transmission of credit shocks evolves across different macroeconomic regimes. While previous studies have examined credit supply disturbances primarily in advanced economies or during conventional financial crises, relatively little evidence exists on how credit shocks propagate during systemic disruptions such as the Covid-19 pandemic.

Methodologically, the paper also contributes to the growing literature that exploits non-Gaussianity and heteroskedasticity to improve structural identification in VAR models. By incorporating higher-order moments and volatility shifts into a sign- and zero-restricted Bayesian SVAR, the analysis illustrates how additional statistical information can sharpen posterior inference within a maintained identification scheme when macro-financial data exhibit fat tails and volatility clustering. These refinements improve precision conditional on the imposed restrictions, but they do not by themselves establish stronger economic identification.

The relationship between credit growth and economic activity in Peru has historically been positive: periods of stronger GDP growth are typically associated with faster credit expansion. This comovement reflects the joint influence of borrower demand, lending conditions, and broader macroeconomic fundamentals.

Figure 1 illustrates this relationship using annual observations for 1997-2024. For most of the sample, credit growth and GDP growth move together closely. The Covid-19 crisis, however, represents a striking deviation from this historical pattern. In 2020, real GDP contracted by about 10.9 percent, while credit to the private sector expanded by about 10.8 percent. This unusual combination coincided with extraordinary policy interventions aimed at preserving financial intermediation and preventing a breakdown in payment chains, most notably the government-backed credit guarantee program.

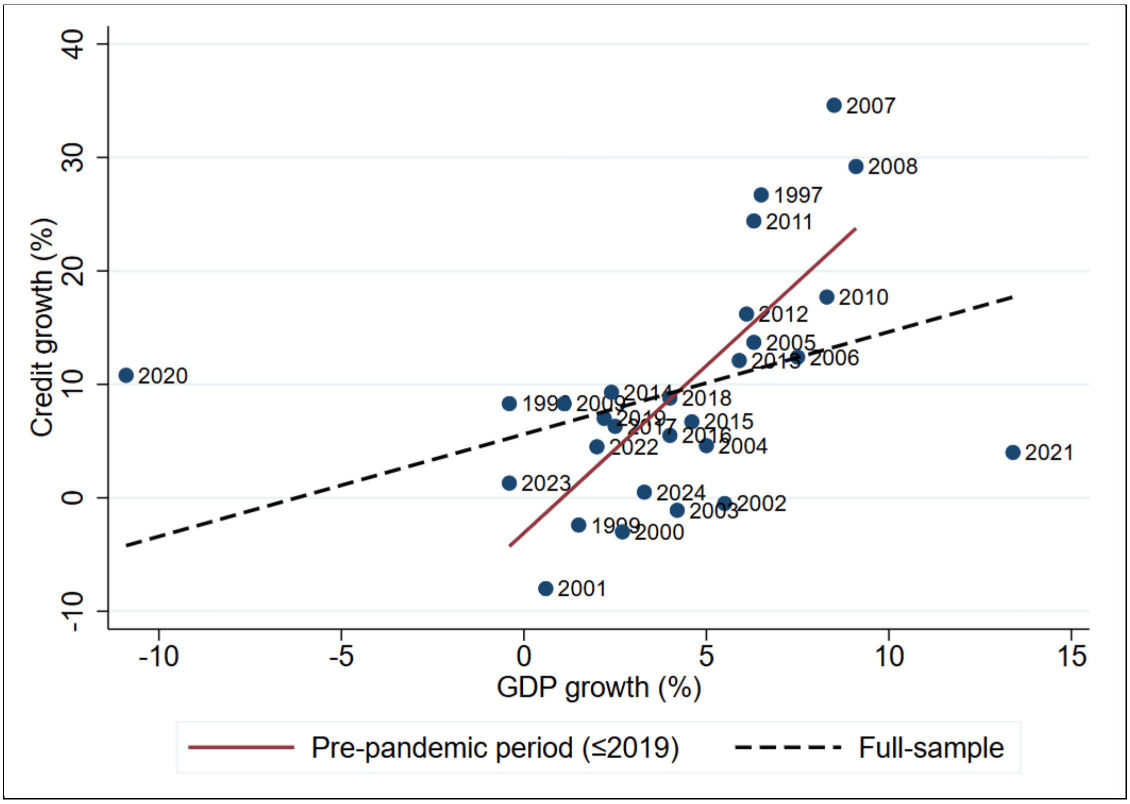
As shown in Figure 1, the 2020 observation lies far outside the historical credit--activity relationship. This suggests that the pandemic was not simply a period of unusually large macroeconomic volatility, but also one in which the role of credit in macroeconomic adjustment may have changed. In particular, credit may have operated as a more active stabilization margin than in previous downturns.

This observation motivates the central question of the paper: did the transmission of credit shocks change during the pandemic period? Addressing this question requires an empirical framework capable of accommodating both the volatility spike associated with Covid-19 and the possibility that macro-financial shocks became fat-tailed and non-Gaussian. Standard Gaussian VAR approaches may be ill-suited for such episodes, as extreme observations can distort inference about structural relationships.

To account for these features, the empirical analysis below employs a Bayesian structural VAR that combines sign and zero restrictions with identification refinements based on heteroskedasticity and higher-order moments. This framework allows us to study whether the transmission of credit supply and demand shocks differed across the pre-pandemic, pandemic, and post-pandemic periods.

More broadly, the episode raises the possibility that large guaranteed-credit programs may be associated not only with changes in the level of credit, but also with changes in the macroeconomic transmission of credit shocks. Since the empirical framework does not separately identify policy-induced shocks, this interpretation should be understood as a possible mechanism rather than as direct evidence of policy effectiveness.

Figure 1: Credit growth and GDP growth in Peru



Note: The figure illustrates the historical relationship between credit growth and economic activity in Peru. While the two variables typically move together, the Covid-19 episode represents a notable deviation from this pattern, raising the question of whether the transmission of credit shocks changed during the pandemic period.

The remainder of the paper is organized as follows. Section 2 reviews the related literature. Section 3 presents the empirical methodology and identification strategy. Section 4 describes the data and model specification. Section 5 reports the empirical results, and section 6 concludes.

2. Literature review

A branch of the literature explores the use of heteroscedasticity and non-Gaussianity assumptions to facilitate statistical identification of shocks. These approaches take advantage of the fact that economic disturbances, especially during periods of heightened uncertainty, often exhibit characteristics such as heavy tails or leptokurtosis. These features can provide additional statistical information by narrowing the range of admissible shock structures within a given set of identifying assumptions. This may lead to more precise impulse-response estimates, although the economic interpretation remains conditional on the maintained restrictions. Recent examples of applications using heteroscedasticity and non-Gaussianity assumptions for shock identification include Lewis (2022, 2024), Brunnermeier et al. (2021), Miescu & Rossi (2021), and Bobeica & Hartwig (2023).

Macroeconomic data, particularly during the pandemic, often exhibit heteroscedasticity and nonGaussianity, characteristics that provide valuable information for shock identification. Within a set-identified SVAR framework, incorporating these assumptions can sharpen posterior inference by reducing the set of admissible models and improving the robustness of the results conditional on the maintained assumptions, as shown in the works of Lenza & Primiceri (2022), Lanne et al. (2023), Lewis (2024), Montiel Olea et al. (2022), and Bobeica & Hartwig (2023). Generally, economic shocks are considered to be leptokurtic, characterized by high kurtosis and long tails in their distributions. This observation is consistent with the work of Acemoglu et al. (2017) who showed that aggregate economic variables often exhibit leptokurtic behavior due to the irregular arrival of shocks. Assuming leptokurtic structural shocks, as suggested by Andrade et al. (2023), helps refine the identification of SVAR models by ensuring they meet sign and zero restrictions.

In the context of BVAR models, the parameters and resulting impulse responses are sensitive to factors such as lag length, sample period, and the choice of priors. Periods of high uncertainty, such as financial crises or pandemics, tend to introduce variations in these parameters. For example, Lenza & Primiceri (2022), Schorfheide & Song (2021) and Carriero et al. (2024) documented that including pandemic-period observations in U.S. data can lead to explosive results in VAR models. The robustness of identification strategies, especially with respect to non-Gaussianity, has been a key area of research. For example, Lanne et al. (2017) and Lanne et al. (2023) demonstrate how non-Gaussian properties can help narrow the set of possible shocks in set-identified models. For Peru, Pozo & Rojas (2023) suggest symmetry in monetary policy shocks. Additionally, Pozo & Rojas (2020) provide evidence of symmetric responses to both expansionary and contractionary monetary policy shocks in the Peruvian credit market. This contrasts with studies such as Agénor (2001) and Olayiwola & Ogun (2019), which identify asymmetric effects.

The analysis of structural shocks in macroeconomic data, particularly those with heavy tails, is crucial for understanding underlying financial disturbances. As noted by Jarociński (2024), such heavy tails may contain critical information about the nature of shocks, for example in events such as Federal Open Market Committee (FOMC) announcements. This highlights the importance of case studies where shocks are informative. The set-identification methodology employed in this study aims to identify a subset of structural models, incorporating relevant economic restrictions. Recent unconventional policy measures in credit markets, implemented by governments in response to the Covid-19 pandemic, could be a source of non-Gaussian shocks. These shocks are characterized by unpredictable, large positive and negative changes, further complicating the estimation process.

Bobeica & Hartwig (2023) shows that VAR parameters are particularly sensitive to data from the post-March 2020 period, emphasizing the need for models that account for fat-tailed residuals rather than assuming a Gaussian distribution. This further underscore the necessity of incorporating nonGaussian features in model estimation to improve robustness, especially during extraordinary periods like the Covid-19 pandemic. The robustness of identification strategies, particularly with respect to non-Gaussianity, has become a key area of research.

For instance, Lanne et al. (2023) demonstrate how non-Gaussian properties can help refine the identification process by reducing the set of possible structural shocks in set-identified models. These advancements provide valuable insights into how shocks propagate through the economy, especially during periods of financial distress.

Another branch of the empirical literature employs time-varying parameter VAR models with stochastic volatility (TVP–VAR–SV), which capture evolving dynamics by allowing both coefficients and shock variances to change over time (see Guevara & Rodríguez, 2020). In contrast, our approach maintains fixed parameters within regimes and attains identification precision through structural restrictions, on signs, zeros, and higher-order moments, while explicitly correcting for heteroskedasticity during the volatility cluster associated with the Covid-19 shock.

Unlike these previous studies, we apply a Bayesian approach that combines heteroskedasticity correction with non-Gaussian robust inference to sharpen inference about credit shocks when the data exhibit volatility spikes and fat-tailed errors. The aim is not to claim that higher-order distributional information independently validates the structural interpretation, but to assess whether it provides useful information conditional on the baseline identifying assumptions.

Furthermore, while the existing literature on credit shocks in emerging economies has focused primarily on normal periods or conventional financial crises, this study covers the Covid-19 pandemic, allowing us to assess whether the transmission of these shocks changed during a period of extreme uncertainty and large credit-support policies.

3. Empirical methodology

We estimate a Bayesian vector autoregression (BVAR) using monthly macro-financial data. The reduced-form VAR of order *p* can be written as:

$$y_t = \Phi_1 y_{t-1} + \cdots + \Phi_p y_{t-p} + \Phi_0 + u_t, \tag{1}$$

where y_t is an $n \times 1$ vector of endogenous variables, Φ_j are $n \times n$ coefficient matrices, and u_t is an $n \times 1$ vector of reduced-form innovations with zero mean and covariance matrix Σ.

Given the relatively short time dimension of the sample and the monthly frequency of the data, the VAR is estimated using Minnesota priors that shrink coefficients toward a random-walk specification. Hyperparameters are calibrated using marginal likelihood maximization following Giannone et al. (2015). Details of the prior specification are reported in Appendix A.

3.1. Identification strategy

Structural shocks are obtained by linking reduced-form innovations to structural disturbances through

$$u_t = \Sigma^{1/2}\, \Omega\, \nu_t, \tag{2}$$

where Ω is an orthonormal rotation matrix and ν_t denotes structural shocks (see Appendix B for details).

We distinguish between credit supply and credit demand disturbances using economically motivated sign and zero restrictions. Following the literature on credit shock identification (e.g., Duchi & Elbourne, 2016; Büyükbaşaran et al., 2022), credit supply shocks are assumed to move credit volumes and lending spreads in opposite directions, while credit demand shocks move both variables in the same direction. In addition, we impose zero restrictions that rule out contemporaneous effects of financial shocks on real activity. These restrictions reflect the assumption that real variables such as GDP respond to financial disturbances with a short delay.[1]

The full set of identifying restrictions is summarized in Table 1.

Table 1: Shocks and restrictions in SVAR

	Credit supply shock	Credit demand shock	Appreciation shock
GDP growth	0	0	
Inflation	0	0	-
Policy rate	0	0	
Spread	-	+	
Credit growth	+	+	
Depreciation	0		-

Note: All restrictions apply to the initial period of the shock (t = 1). (+) values imply that the shock will affect the corresponding variable positively, (-) values imply that the shock will affect the corresponding variable negatively. (0) means there will be no simultaneous effect of the shock on the corresponding variable. Blank cells imply that there are no restrictions for the shock-variable combination.

3.2. Accounting for pandemic volatility

The Covid-19 pandemic was associated with an unusually large spike in macroeconomic and financial volatility. To account for this feature, we follow the heteroskedasticity adjustment proposed by Lenza & Primiceri (2022). Specifically, we allow the variance of the reduced-form innovations to increase temporarily during the initial phase of the pandemic. This approach

[1] The identification strategy assumes that financial shocks do not affect real activity contemporaneously, which is implemented through zero restrictions on GDP. This assumption follows standard practice in the credit VAR literature. However, it may be more restrictive during crisis episodes when financial disruptions can propagate rapidly to the real economy. As a sensitivity check, we considered alternative identification schemes that relax the contemporaneous zero restriction on GDP. The main qualitative finding, a stronger GDP response to credit supply shocks when pandemic observations are included, remains broadly unchanged. However, the magnitude and short-horizon precision of the responses are affected, indicating that the combination of the credit-volume/spread restrictions and the treatment of pandemic volatility is particularly informative for the baseline results.

captures the short-lived volatility cluster observed in early 2020 without altering the dynamic structure of the VAR. In practice, the volatility scaling is applied to the March–May 2020 period, when macro-financial uncertainty increased sharply. The formal specification of the heteroskedastic model is described in Appendix C.

3.3. Robust identification using higher moments

Standard sign-restricted VARs rely primarily on second-moment information and may generate wide identified sets when shocks exhibit non-Gaussian features. To refine identification, we incorporate additional restrictions based on higher-order moments of the structural shocks. Following Andrade et al. (2023), we exploit information contained in skewness and excess kurtosis to further restrict admissible rotations of the structural system. These moment conditions help reduce the size of the identified set and improve the precision of impulse response estimates. Importantly, this gain in precision should be interpreted as conditional on the maintained identifying assumptions. Tighter credible sets do not, by themselves, constitute independent evidence that the economic labeling of the shocks is more strongly identified. The detailed implementation of the higher-moment identification procedure follows Petrova (2022) and is described in Appendix D.

3.4. Estimation and implementation

The VAR includes six endogenous variables and is estimated with six lags. Lag selection is guided by standard information criteria and marginal likelihood comparisons. While higher lag orders slightly improve in-sample fit, the six-lag specification provides a good compromise between dynamic flexibility and parameter parsimony. Posterior inference is based on 20,000 draws from the reduced-form posterior distribution, discarding the first 5,000 draws as burn-in. Structural identification proceeds by sampling orthonormal rotation matrices following Rubio-Ramírez et al. (2010) and retaining only those draws that satisfy the imposed sign, zero, and higher-moment restrictions. All estimation and identification procedures are implemented using the BVAR toolbox of Canova and Ferroni (2021). Additional computational details are provided in Appendix E.

4. Data

We work with a sample covering the period from August 2010 to August 2024 for the Peruvian economy. We restrict the sample due to the availability of lending and deposit rate series. Given the short sample, our analysis employs a Bayesian framework that could identify the effect of credit shocks in a small open economy with a minimum number of variables.

The SVAR model incorporates a vector of six macro-financial variables: real GDP, inflation rate, policy interest rate, stock of credit in local currency, credit spread in local currency (measured as the difference between lending and deposit rates), and exchange rate depreciation. All variables are included in monthly frequency. The inclusion of the exchange rate is crucial for capturing the effects of capital flows, which play a significant role in driving credit markets in emerging economies. This variable selection follows standard practice for identifying credit market shocks, as demonstrated in studies by Barnett & Thomas (2014), Duchi & Elbourne (2016), Büyükbaşaran et al. (2022), among others.

The data used to characterize the Peruvian credit market are sourced from the Central Bank of Peru's database. These series are transformed into 12-month percentage changes, except for the policy rate and credit spread, which are expressed in annual percentage rates. Monthly data are employed to better capture the shocks associated with financial cycles, which are typically more volatile and shorter in duration than economic cycles (Borio, 2014). The data we used are depicted in Figure 2.

Table 2 provides a statistical summary of these variables. All variables display deviations from normality, as evidenced in the Jarque-Bera test results. Additionally, the Augmented Dickey-Fuller (ADF) tests suggest that most variables are non-stationary, highlighting the importance of Bayesian methods for addressing non-stationarity. The use of the Minnesota prior, which incorporates prior beliefs about the dynamics of the variables, and the sum-of-coefficients prior, which ensures a degree of persistence in the model, enhances the robustness of the SVAR estimates.

Figure 2: Time-series plots for Peruvian macroeconomic variables

Note: Series are in 12-month percentage changes, except for the policy rate and spread, which are in annual percentage rates.

Table 2: Statistical description of variables

	Mean	Median	Max.	Min.	Std.D.	Jarque-Bera	ADF	Obs.
GDP growth	3.4767	3.5178	14.5316	-11.7869	4.539464	99.555***	-3.391(13)***	170
Inflation	3.4744	3.0666	8.8126	0.3631	1.863396	76.622***	-1.641(1)	170
Policy rate	3.7806	3.9708	7.7612	0.1106	1.828975	0.777	-2.324(3)	170
Spread	13.3017	13.3382	17.141	9.711	2.136314	8.816*	-1.774(2)	170
Credit growth	13.1063	11.8623	29.4644	-0.4351	8.168868	9.712***	-2.075(3)	170
Depreciation	2.0906	1.0510	15.5324	-7.7414	5.681246	13.141***	-2.263(0)	170

*Notes: *** denotes significance at 1%, ** at 5%, * at 10%. ADF denotes the ADF unit root test and the optimal lag order in the ADF based on the Schwarz Info criterion are shown in parentheses.*

5. Results

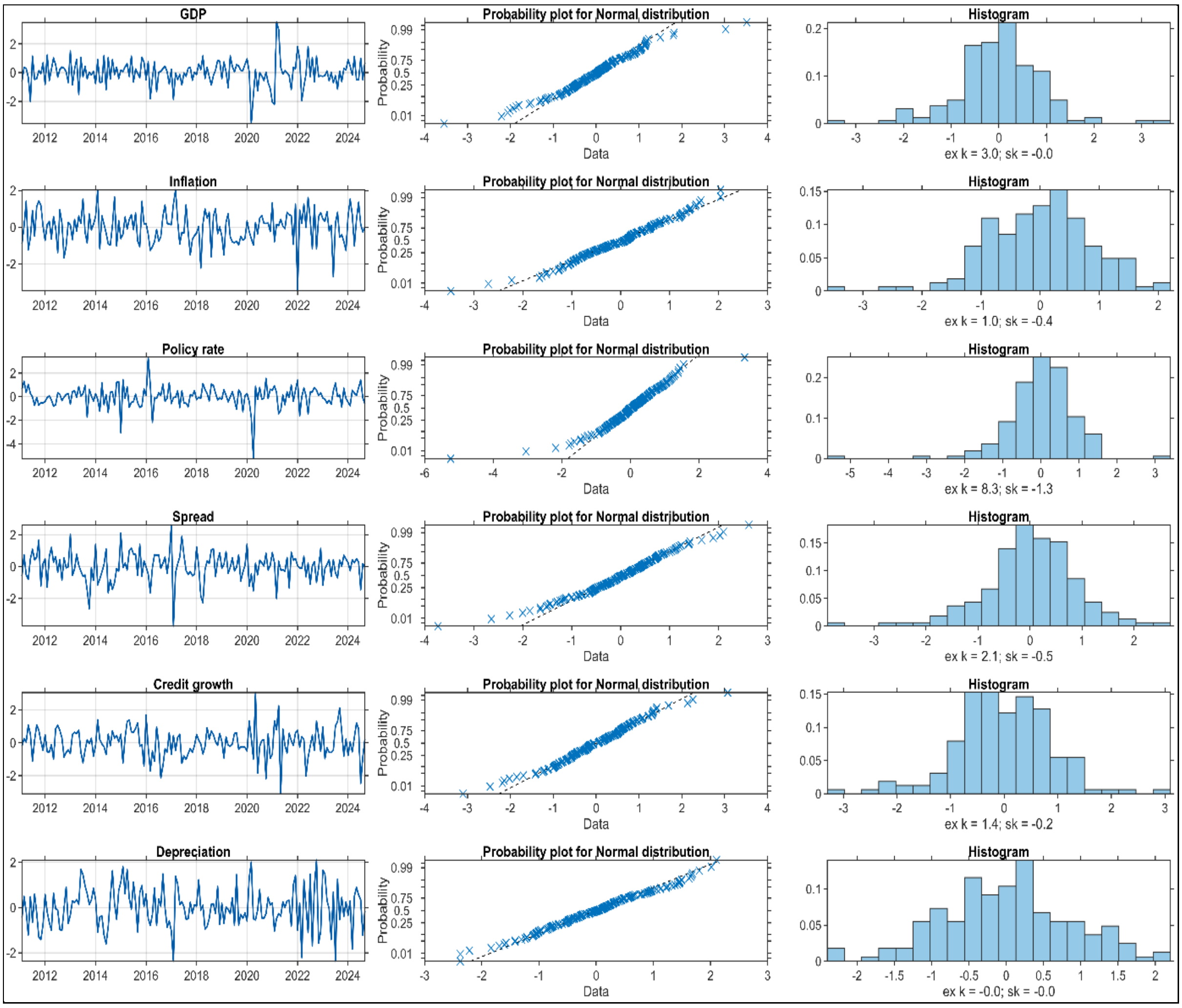
5.1. Evidence on non-Gaussian disturbances

Before turning to structural results, we assess whether the reduced-form innovations exhibit the non-Gaussian features that motivate the robust identification strategy. Figure 3 shows the orthogonalized residuals from the baseline VAR together with graphical evidence on their distributional properties, while Table 3 reports Kolmogorov-Smirnov test statistics.

Two findings stand out. First, several residuals, particularly those associated with GDP, the policy rate, and the credit spread display visible departures from Gaussianity. Second, these departures are driven primarily by excess kurtosis rather than skewness: the robust skewness measures (sk) remain close to zero, whereas excess kurtosis (ex k) is substantial for several variables. This pattern is consistent with the view that the pandemic period was characterized by fat-tailed disturbances and volatility clustering rather than by systematic asymmetry. This finding is consistent with the literature suggesting that economic shocks are generally expected to be leptokurtic, such as Acemoglu et al. (2017) and Lanne et al. (2023), among others.

These results do not by themselves validate the identifying assumptions, but they do suggest that higher-order moments contain potentially useful information for structural identification in this setting. For this reason, the remainder of the analysis compares conventional sign- and zero-restricted results with specifications that additionally account for heteroskedasticity and non-Gaussian shocks.

Figure 3: Orthogonalized residuals derived from the VAR model for six macroeconomic variables: GDP, inflation, policy rate, spread, credit growth, and depreciation



Note: Robust estimations of skewness (sk) and excess of kurtosis (ex k) are shown in the third column.

Table 3: Kolmogorov-Smirnov Test Results

	KS Statistic
GDP	0.10156*
Inflation	0.05772
Policy rate	0.10529**
Spread	0.09702*
Credit growth	0.07301
Depreciation	0.05935

*Notes: *** denotes significance at 1%, ** at 5%, * at 10%. The critical value for the Kolmogorov-Smirnov test is 0.10498.*

5.2. Baseline transmission before the pandemic

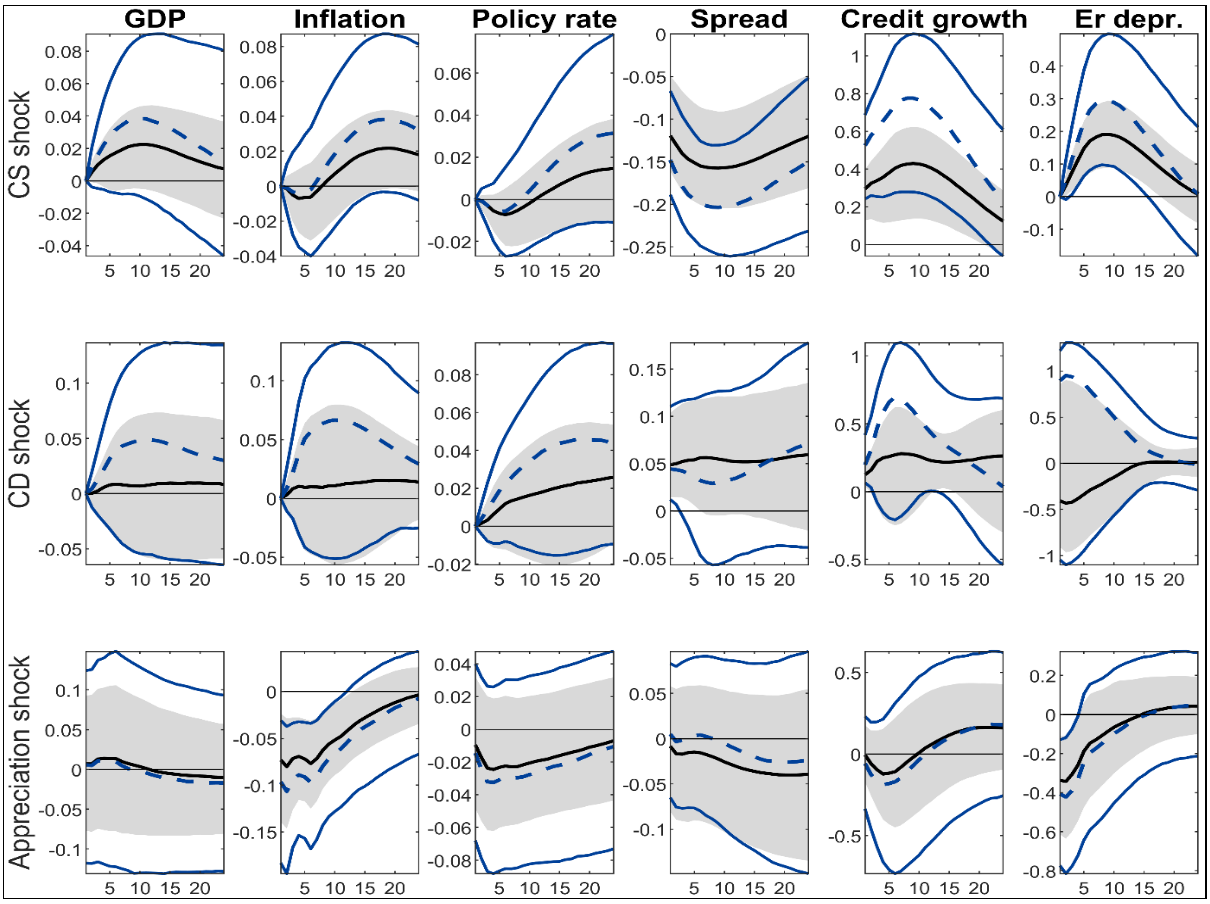
We begin by estimating the model over the pre-pandemic sample (August 2010 to February 2020) to characterize the benchmark transmission of credit shocks under relatively normal macro-financial conditions. Figure 4 reports the impulse response functions (IRFs) to credit supply, credit demand, and appreciation shocks. These represent 68% credible set identified using sign and zero restrictions on key macroeconomic variables.

For a credit supply shock, the median response of GDP is positive, indicating an expansionary effect on economic activity. Additionally, inflation and the policy rate exhibit a slight upward adjustment starting around the sixth period, reflecting the potential pass-through effects of increased credit availability. Notably, the domestic currency depreciates significantly following a positive credit supply shock, a phenomenon that can be linked to the monetary theory of credit creation, where the expansion of credit exerts downward pressure on the local currency's value.

By contrast, credit demand shocks produce more modest and less persistent responses. The median response of GDP is positive, indicating that higher credit demand stimulates economic growth. Inflation shows a mild increase, while the policy rate adjusts upward, reflecting the central bank's response to higher demand pressures. In the case of an appreciation shock, GDP initially rises modestly, driven by short-term gains from lower import prices, but subsequently declines as export competitiveness diminishes. The policy rate decreases in response to deflationary tendencies. Credit growth exhibits a moderate decline, and the credit spread narrows slightly, suggesting limited effects on the credit market.

Introducing higher-moment restrictions leaves the qualitative pattern of the impulse responses broadly unchanged but reduces the size of the identified set. This result suggests that the additional moment information sharpens posterior inference conditional on the maintained identifying assumptions, without fundamentally altering the economic interpretation of the shocks in the pre-pandemic sample. The tighter credible sets should therefore be interpreted as gains in statistical precision within the specified identification scheme, rather than as independent evidence of stronger economic identification.

Figure 4: Impulse response functions (IRFs) to credit supply, credit demand, and appreciation shocks (before pandemic)



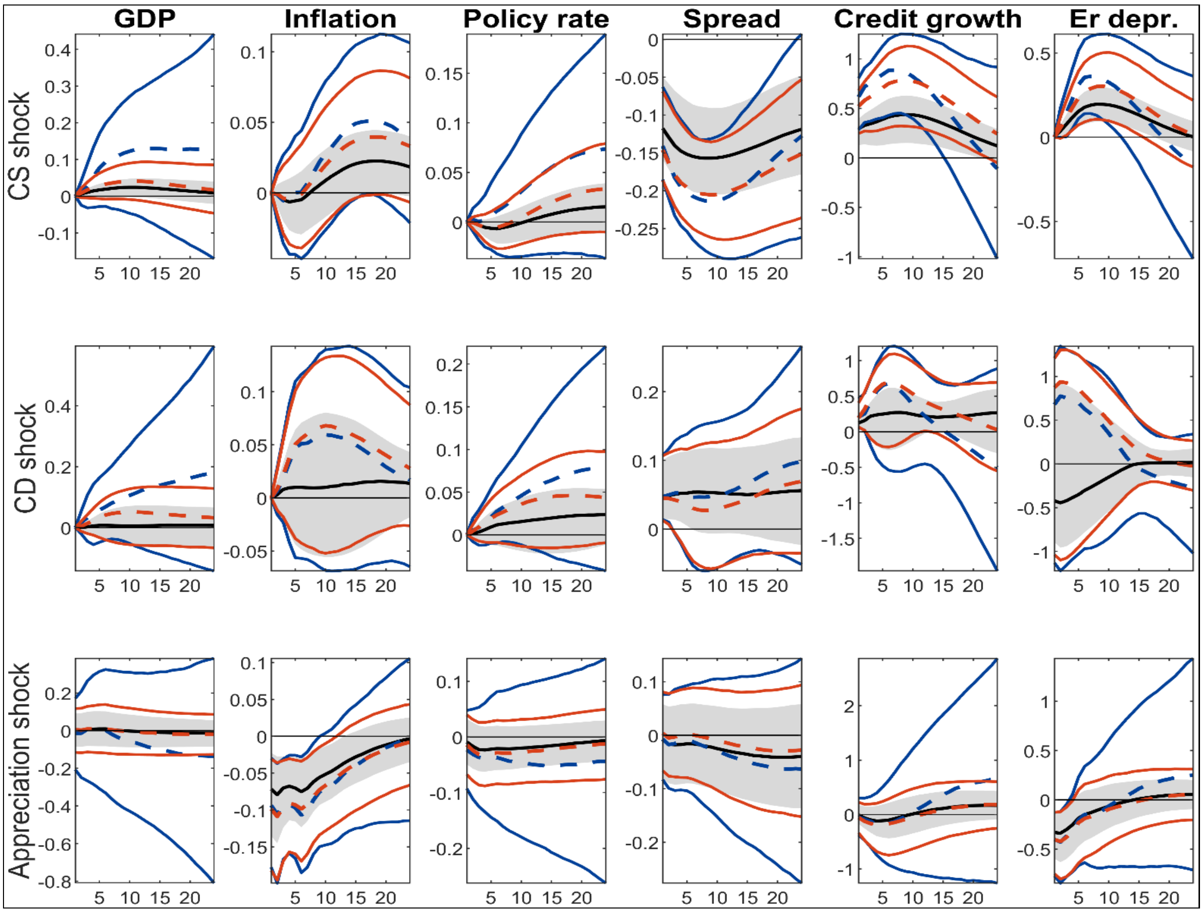
Sample period: August 2010 to February 2020 (before pandemic). (Solid, Blue Line) 68% identified set from a Bayesian SVAR with sign and zero restrictions and optimally selected Minnesota prior hyperparameters. (Shaded, Gray Area) Same as above, with additional non-Gaussian shock assumptions. Note: CS stands for credit supply, and CD stands for credit demand.

5.3. Did the transmission of credit shocks change during the pandemic?

We next extend the sample to include the pandemic period. The central question is whether credit shocks propagated differently once the economy was hit by extreme volatility and large credit policy interventions.

The inclusion of Covid-19 observations significantly alters the estimated IRFs compared to the pre-Covid period. Specifically, the IRFs in Figure 5 exhibit stronger responses to the same shocks, with particularly pronounced effects on GDP and credit growth under credit supply and credit demand shocks, as well as on exchange rate depreciation following an appreciation shock. The red line represents results corrected for heteroskedasticity during high-volatility months, following the methodology of Lenza & Primiceri (2022). This correction notably affects the IRFs for GDP, the policy rate, and credit growth. Additionally, accounting for non-Gaussian shocks further narrows the credible sets. These findings are consistent with the view that pandemic-era volatility changed macro-financial dynamics, motivating the use of specifications that explicitly account for volatility shifts and fat-tailed disturbances. The IRFs reveal varying degrees of persistence across periods and shocks. In particular, the effects of credit supply shocks on GDP and credit growth remain positive and persistent for several months after the initial impact, suggesting that credit expansions continue to stimulate real activity beyond the short term. Conversely, the responses to credit demand shocks tend to dissipate more rapidly, consistent with temporary demand-driven fluctuations rather than sustained effects. Regarding the graphical presentation, the solid blue lines represent the median responses obtained from the Bayesian SVAR with sign and zero restrictions under optimal Minnesota priors. The solid red lines correspond to the same specification corrected for heteroskedasticity during the high-volatility cluster (March–May 2020). The shaded gray areas illustrate the identified credible sets when excess kurtosis (non-Gaussian) restrictions are imposed. Finally, the black lines indicate the actual or baseline responses used for comparison across specifications.

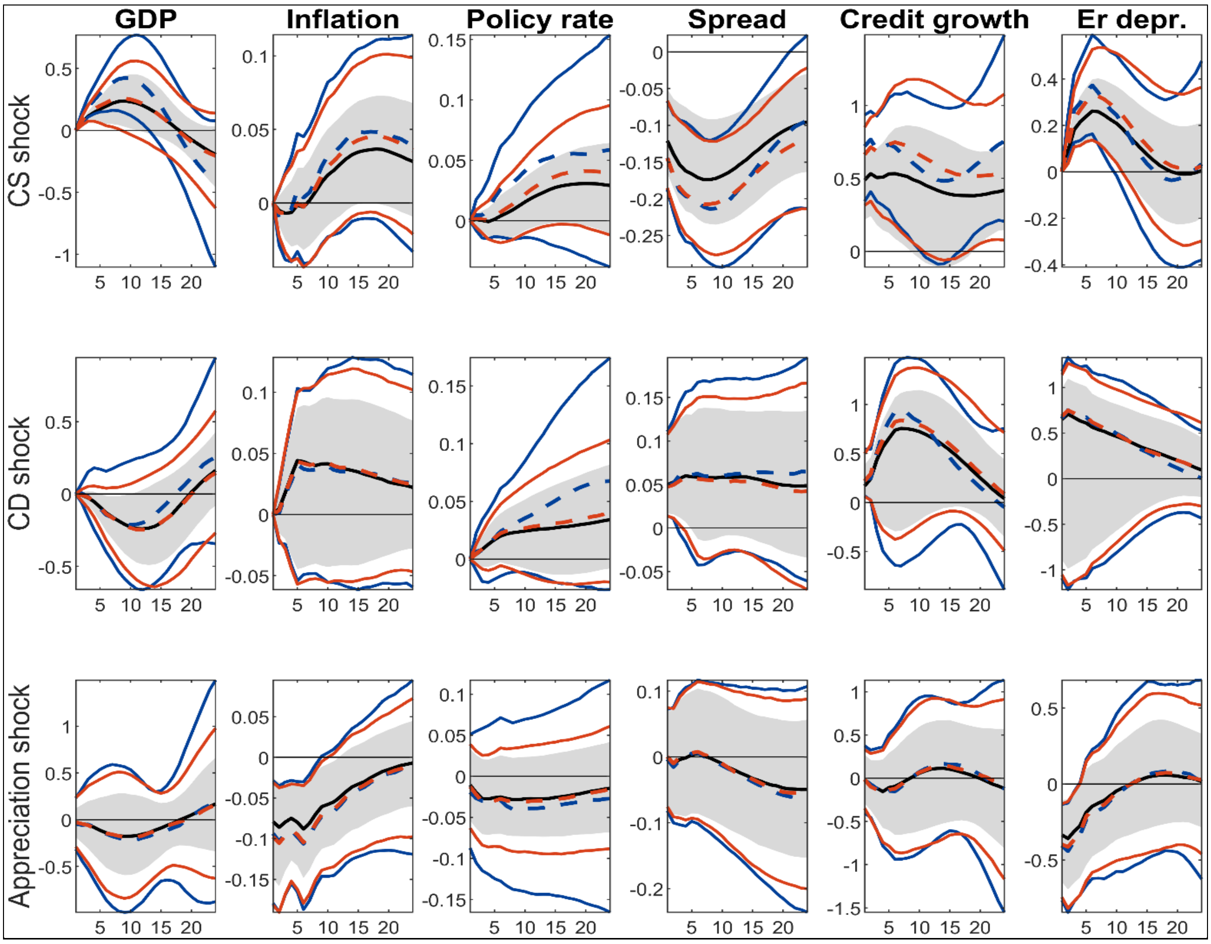
Figure 5: Impulse response functions (IRFs) to credit supply, credit demand, and appreciation shocks (including pandemic)



Sample period: August 2010 to May 2020 (including pandemic). (Solid, Blue Line) 68% identified set from a Bayesian SVAR with sign and zero restrictions and optimally selected Minnesota prior hyperparameters. (Solid, Red Line) Same as above, corrected for heteroskedasticity during high-volatility clusters (March–May 2020), following Lenza & Primiceri (2022). (Shaded, Gray Area) Same as above, with additional non-Gaussian shock assumptions. Note: CS stands for credit supply, and CD stands for credit demand.

Figure 6 extends the sample period to May 2021, incorporating 12 months of data compared to earlier figures. This extension captures the immediate aftermath of the Covid-19 pandemic. The IRF for the credit supply shock now exhibits positive responses of GDP in the initial periods. This marks a notable shift compared to pre-pandemic estimates, where the effects on GDP were less pronounced. The stronger response suggests that economic activity became more responsive to credit supply conditions during the pandemic, likely reflecting heightened reliance on credit availability amid elevated uncertainty and economic disruptions. The amplified response may also be consistent with the presence of expansionary credit and liquidity policies implemented during the pandemic, which may have helped sustain credit flows. However, because the model does not separately identify policy-induced credit shocks, this interpretation should be viewed as a possible mechanism rather than as direct evidence that such policies caused the stronger GDP response.

Figure 6: Impulse response functions (IRFs) to credit supply, credit demand, and appreciation shocks (including pandemic aftermath)

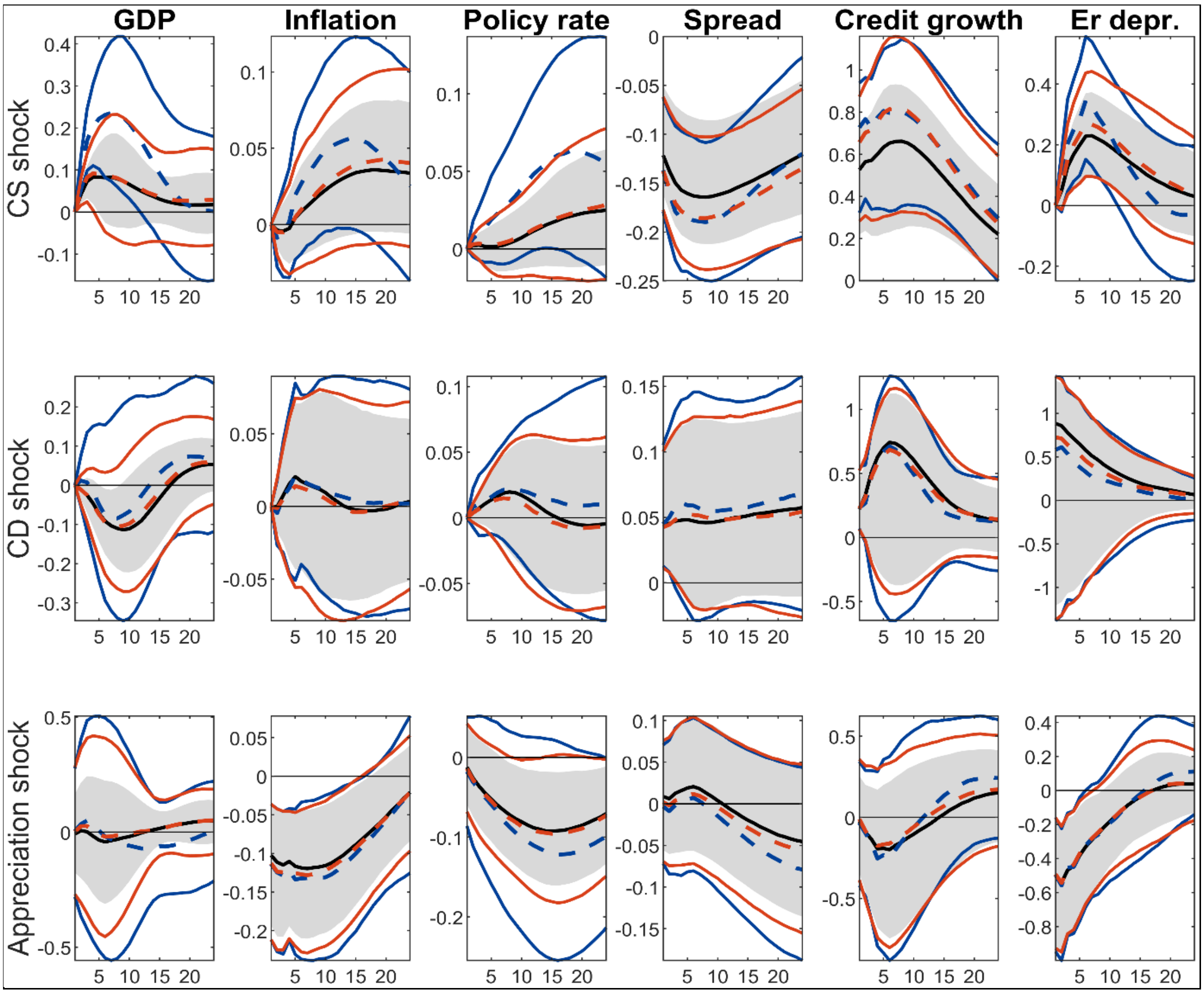


Sample period: August 2010 to May 2021 (including pandemic). (Solid, Blue Line) 68% identified set from a Bayesian SVAR with sign and zero restrictions and optimally selected Minnesota prior hyperparameters. (Solid, Red Line) Same as above, corrected for heteroskedasticity during high-volatility clusters (March–May 2020), following Lenza & Primiceri (2022). (Shaded, Gray Area) Same as above, with additional non-Gaussian shock assumptions. Note: CS stands for credit supply, and CD stands for credit demand.

Figure 7 presents the complete dataset. The refinements introduced by accounting for heteroskedasticity and non-Gaussian shocks further improve the precision of the identified set. The positive response of GDP to credit supply shocks in the post-pandemic period suggests that credit conditions became more closely associated with real activity during and after the pandemic. This pattern is consistent with several possible mechanisms, including increased reliance on bank credit, heightened macro-financial uncertainty, and the presence of domestic credit and liquidity support measures. However, the empirical framework does not distinguish policy-induced credit shocks from other credit-supply disturbances, so the results should not be interpreted as a direct evaluation of those policies. In contrast, the contractionary effects of credit demand shocks on GDP during the same period suggest that credit constraints were limiting demand for credit, thereby suppressing economic activity.

The stronger responses observed during this period are consistent with several, not mutually exclusive, mechanisms: heightened macro-financial uncertainty, increased firm reliance on bank credit, state-dependent amplification, and the presence of large guaranteed credit programs such as Reactiva Perú. Because the empirical framework does not separately identify policy-induced credit shocks, these results should be interpreted as evidence of a changing transmission mechanism rather than as a direct evaluation of policy effectiveness.

Figure 7: Impulse response functions (IRFs) to credit supply, credit demand, and appreciation shocks (all data)



Sample period: August 2010 to August 2024 (All data). (Solid, Blue Line) 68% identified set from a Bayesian SVAR with sign and zero restrictions and optimally selected Minnesota prior hyperparameters. (Solid, Red Line) Same as above, corrected for heteroskedasticity during high-volatility clusters (March–May 2020), following Lenza & Primiceri (2022). (Shaded, Gray Area) Same as above, with additional non-Gaussian shock assumptions. Note: CS stands for credit supply, and CD stands for credit demand.

5.4. Comparing impulse responses across estimation samples

We compare impulse responses across three estimation samples: the pre-pandemic sample (ending in February 2020), an extended sample through May 2021 that includes the pandemic period, and the full sample through August 2024. For each horizon, we compute the posterior distribution of the difference between the impulse responses obtained from these alternative samples. This exercise allows us to assess whether the stronger responses observed when pandemic and later observations are incorporated reflect systematic changes in transmission rather than estimation variability.

The results indicate that the sample through May 2021 delivers a stronger GDP response to credit supply shocks than the pre-pandemic sample at short and intermediate horizons. The posterior median difference is positive throughout the early part of the impulse-response path, the credible interval excludes zero at horizons 1 and 3, and the posterior probability that the response is larger exceeds 0.95 at those horizons. When the full sample through August 2024 is compared with the pre-pandemic sample, the posterior median difference also remains positive, but the evidence is weaker and becomes less precise as the horizon increases.

Comparing the full sample with the sample through May 2021 shows that the stronger response is concentrated around the pandemic and immediate recovery phase. The posterior median difference is negative at short and intermediate horizons, indicating that the full-sample response is generally smaller than the response estimated in the sample that gives greater weight to the pandemic episode and its aftermath. Taken together, these results suggest that the amplification of credit supply shocks was strongest around the pandemic period and became less pronounced once later observations were incorporated.

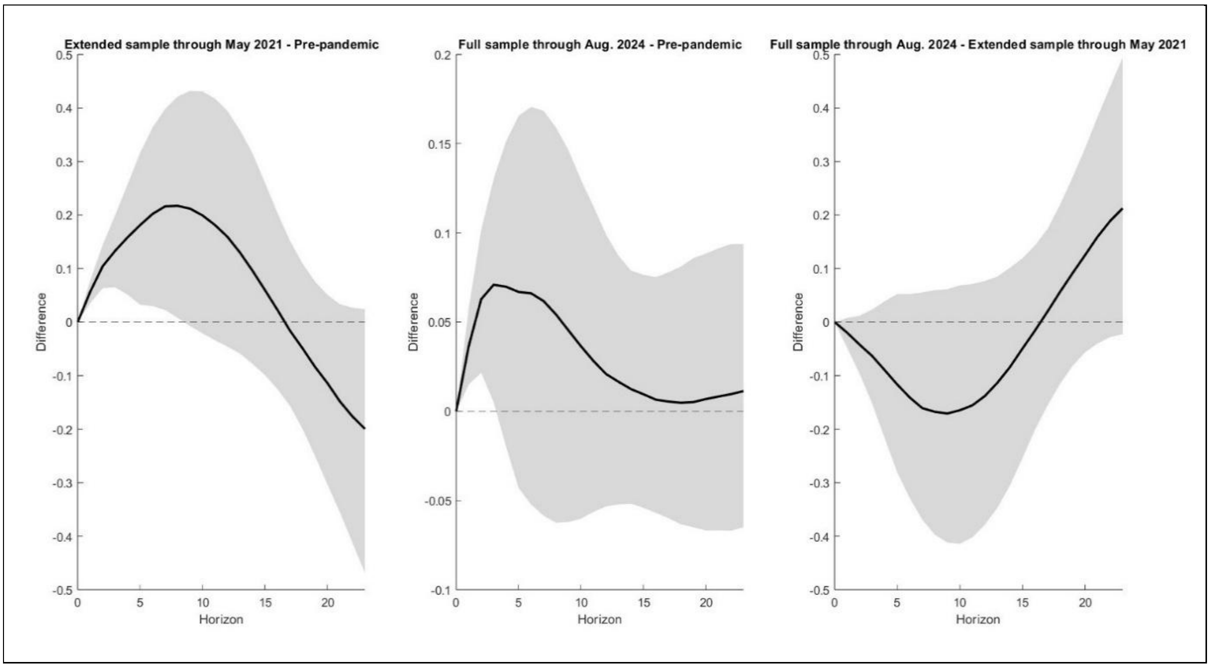
Table 4 reports the corresponding posterior comparisons, while Figure 8 plots the posterior median difference together with its credible band. Consistent with the table, the sample through May 2021 tends to generate a stronger response than the pre-pandemic sample, especially at short horizons. The full sample through August 2024 also exhibits a more positive response than the pre-pandemic sample, although the difference is smaller and less precisely estimated. Overall, the formal posterior comparison supports the view that, under the maintained identifying assumptions, the estimated GDP response to credit supply shocks was stronger around the pandemic episode. This evidence points to a change in the estimated transmission of credit conditions, while remaining conditional on the baseline identification scheme and the treatment of pandemic volatility.

Table 4: Posterior comparison of GDP impulse responses to a credit supply shock across estimation samples

Comparison sample	Horizon	Median diff.	Lower band	Upper band	$P(\Delta_h > 0)$
Through May 2021 versus Pre-pandemic sample	0	0.000	0.000	0.000	0.486
	1	0.056	0.035	0.078	0.996
	3	0.133	0.065	0.200	0.979
	6	0.202	0.030	0.364	0.885
	9	0.212	-0.007	0.432	0.831
	12	0.159	-0.046	0.394	0.774
	18	-0.049	-0.199	0.110	0.370
Full sample versus Pre-pandemic sample	0	0.000	0.000	0.000	0.476
	1	0.036	0.015	0.057	0.953
	3	0.071	0.005	0.130	0.861
	6	0.066	-0.052	0.171	0.709
	9	0.045	-0.062	0.146	0.658
	12	0.021	-0.053	0.099	0.614
	18	0.005	-0.063	0.081	0.526
Full sample versus sample through May 2021	0	0.000	0.000	0.000	0.466
	1	-0.020	-0.048	0.008	0.240
	3	-0.064	-0.153	0.024	0.234
	6	-0.141	-0.329	0.052	0.238
	9	-0.171	-0.412	0.061	0.237
	12	-0.138	-0.379	0.077	0.264
	18	0.056	-0.116	0.219	0.639

Notes: The table reports posterior comparisons of the GDP impulse response to a credit supply shock across alternative estimation samples. For each horizon h, Δ_h denotes the difference between the impulse response estimated in the first sample listed in each panel and the corresponding response estimated in the second sample. "Median diff." is the posterior median of Δ_h, while "Lower band" and "Upper band" report the bounds of the posterior credible interval. The last column reports the posterior probability that the response in the first sample exceeds the response in the second sample, $P(\Delta_h > 0)$.

Figure 8: Posterior differences in the GDP impulse response to a credit supply shock across estimation samples



Note: The solid line denotes the posterior median of the difference in impulse responses, and the shaded area represents the posterior credible band. Values above zero indicate that the response in the first sample listed in each panel is larger than the corresponding response in the second sample. The left panel compares the sample through May 2021 with the pre-pandemic sample, the middle panel compares the full sample through August 2024 with the pre-pandemic sample, and the right panel compares the full sample with the sample through May 2021.

5.5. Sensitivity to alternative identifying restrictions

The sensitivity analysis suggests that the baseline findings are not mechanically driven by the contemporaneous zero restriction on GDP. Relaxing this restriction changes the short-horizon magnitude and precision of the responses, but it does not overturn the qualitative pattern that the GDP response to credit supply shocks becomes stronger when pandemic observations are included. The restrictions on credit volumes and spreads remain central for distinguishing credit supply from credit demand disturbances, while the heteroskedasticity correction is most informative during the high-volatility months associated with the pandemic. Higher-order distributional information mainly sharpens the credible sets rather than changing the sign or broad timing of the impulse responses. Hence, the baseline results should be interpreted as reflecting the joint role of economically motivated credit-market restrictions and statistical information from pandemic-era volatility and fat-tailed disturbances.

Appendix Figure B.1 illustrates this point by comparing the GDP response to a credit supply shock under the baseline identification scheme and under the alternative specification that relaxes the contemporaneous zero restriction on GDP. The median response remains positive and hump-shaped, although the relaxed specification produces a larger short-horizon response and wider credible sets. This indicates that the zero restriction helps discipline short-run inference, but the positive GDP response is not mechanically generated by imposing a contemporaneous zero effect.

5.6. Variance decomposition and economic interpretation

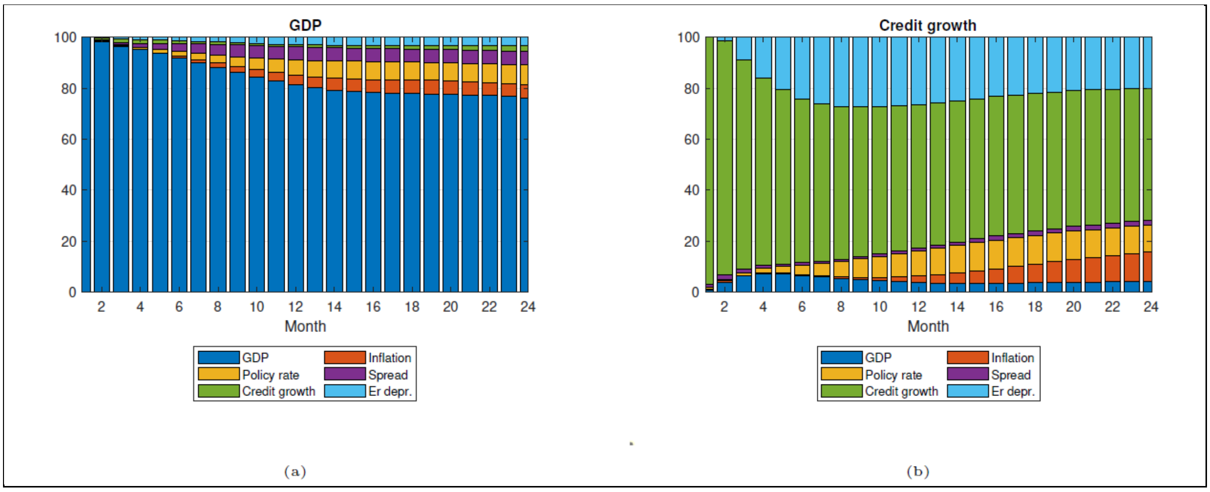
Figure 9 reports the forecast error variance decomposition for GDP and credit growth. The results complement the impulse responses by showing the relative importance of different shocks over the forecast horizon.

For GDP, own innovations account for most of the forecast error variance even at longer horizons, indicating that aggregate activity remains largely driven by broader macroeconomic forces rather than by short-run financial disturbances alone. Credit-related and exchange-rate-related shocks play a secondary role, although their contribution increases gradually over time.

For credit growth, the picture is different. Financial variables—especially spreads and exchange-rate depreciation—account for a substantial share of medium-term fluctuations, highlighting the importance of balance-sheet conditions and external financial factors in the propagation of credit disturbances.

Taken together, these results suggest that credit shocks matter more for the dynamics of financial variables than for the short-run variance of aggregate output, even though the impulse responses show that credit supply disturbances can still have economically meaningful effects on activity.

Figure 9: Forecast error variance decomposition for (a) GDP and (b) credit growth



Note: Bars show the share of the forecast error variance explained by each structural shock (GDP, policy rate, inflation, spread, credit growth, and exchange rate depreciation) over horizons from 1 to 24 months, based on the baseline BVAR with optimally selected Minnesota prior hyperparameters.

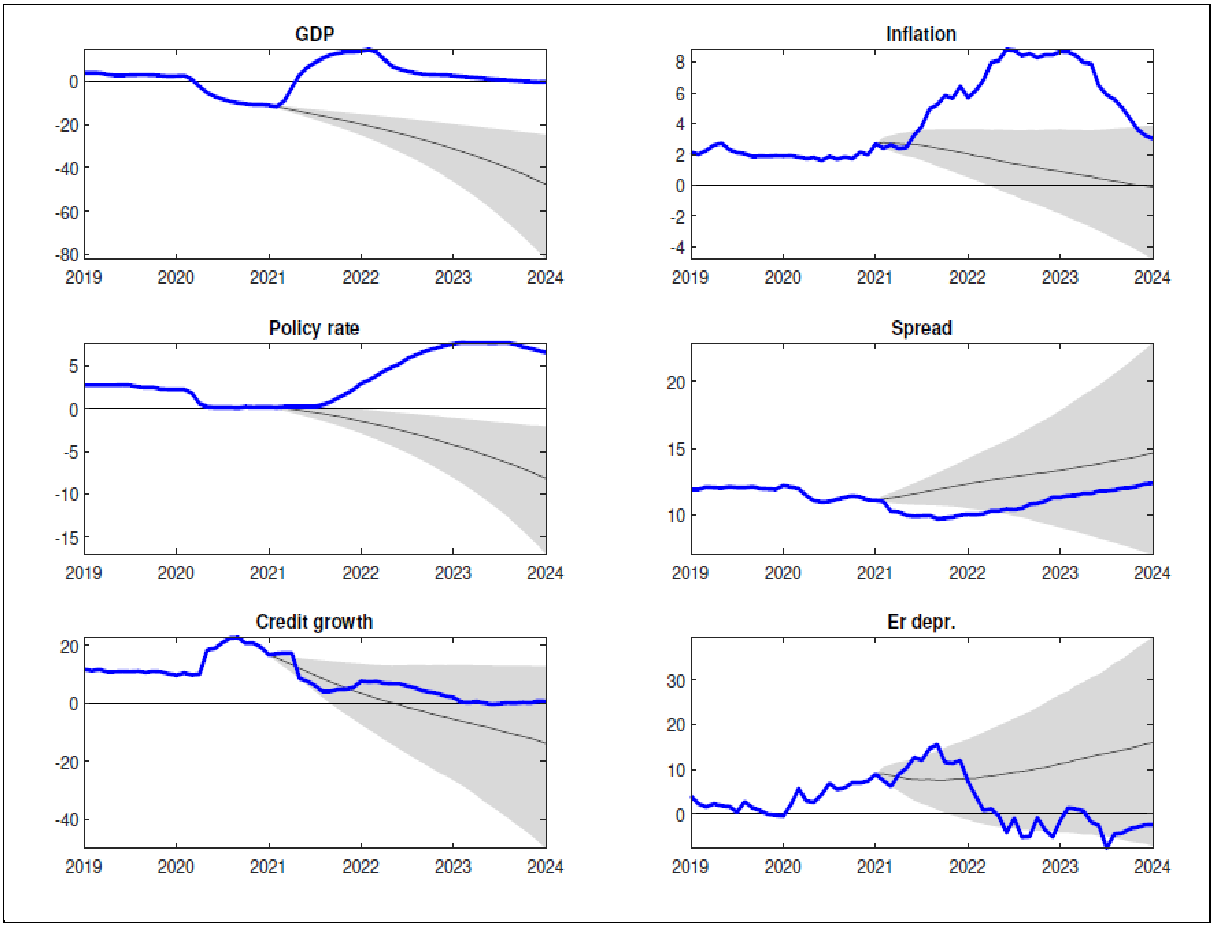
5.7. Forecast performance

As a complementary exercise, we evaluate whether the heteroskedastic and non-Gaussian specifications improve density forecasting performance when pandemic observations are included in estimation. This exercise is useful from a central-banking perspective because it assesses whether the proposed refinements better capture the unusual statistical properties of the data. However, improved forecast performance should not be interpreted as independent validation of the structural interpretation of the shocks.

Figures 10-12 report fan charts for the main specifications, and Table 5 summarizes the corresponding log predictive scores. The benchmark Gaussian specification produces wide forecast intervals and tracks the post-pandemic evolution of some variables only imprecisely. Allowing for heteroskedasticity narrows the predictive distributions for several variables, while the specification that additionally allows for non-Gaussian reduced-form innovations generally delivers the best overall density forecasts.

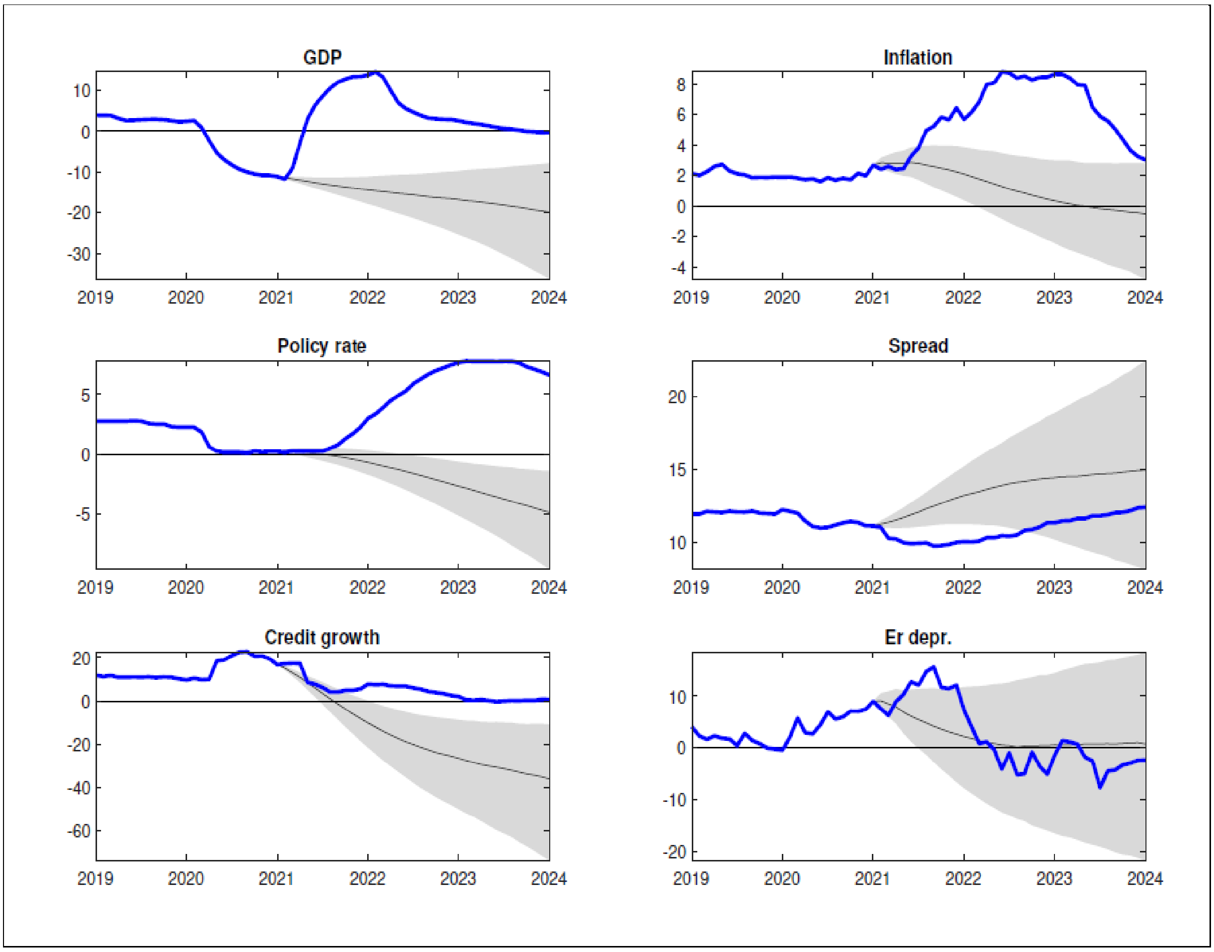
Across most variables and horizons, the model combining volatility adjustment with a non-Gaussian error specification performs best in terms of log predictive scores. This result suggests that accounting for pandemic-era outliers and fat tails improves the statistical fit and density forecasting performance of the model. However, predictive performance and structural identification answer different questions. The forecasting exercise evaluates how well the model captures the distribution of the observed data; it does not provide independent validation of the economic labeling of the identified shocks, which remains tied to the imposed sign, zero, heteroskedasticity, and higher-moment restrictions.

Figure 10: Fan charts for main variables under benchmark model



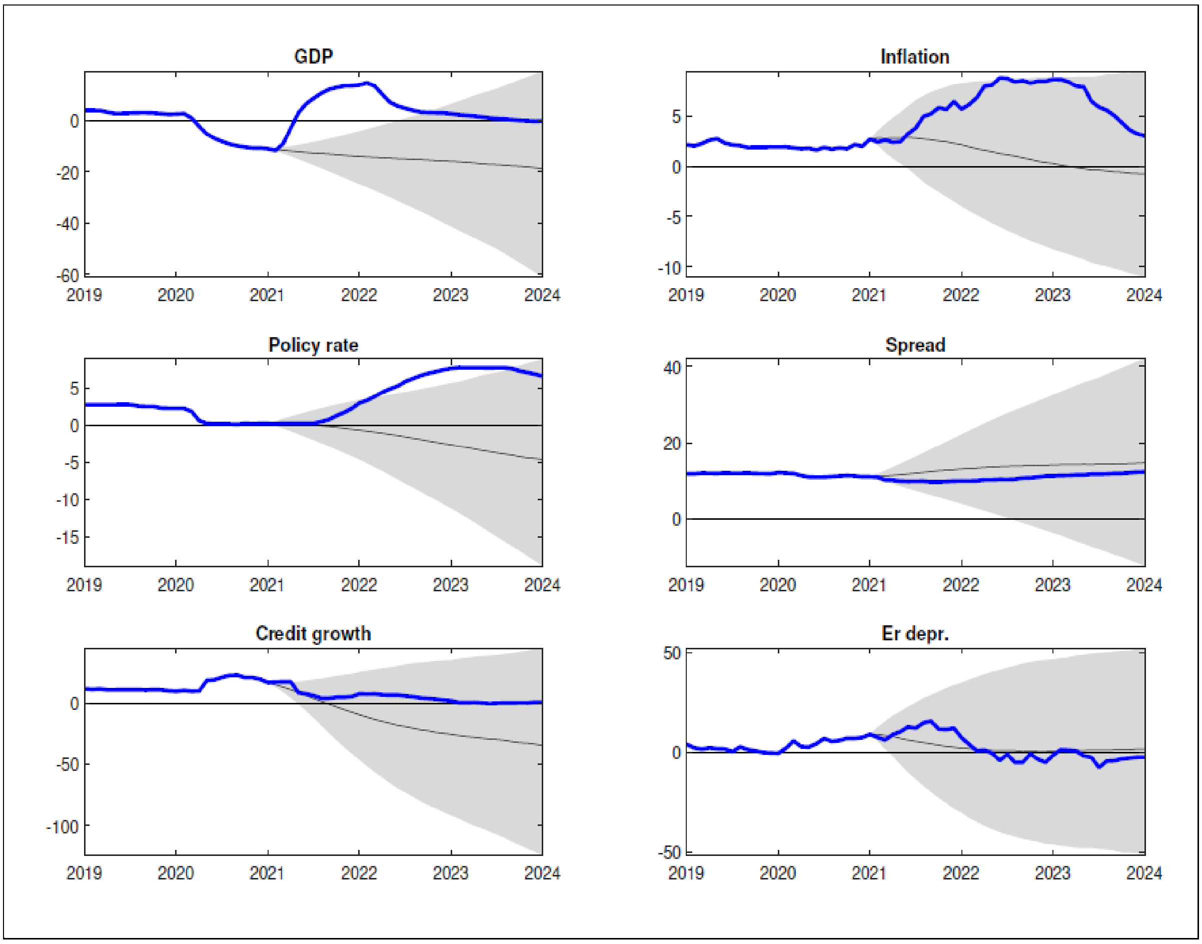
Note: Fan charts starting in January 2021, with optimal Minnesota Prior. The light gray bands denote 68% credible sets. The blue line corresponds to the actual data.

Figure 11: Fan charts for main variables under the model corrected for heteroskedasticity



Note: Fan charts starting in January 2021, with optimal Minnesota Prior of a BVAR corrected for heteroskedasticity when high volatility cluster occurs at March, April and May 2020, along the lines of Lenza & Primiceri (2022). The light gray bands denote 68% credible sets. The blue line corresponds to the actual data.

Figure 12: Fan charts for main variables under the model corrected for heteroskedasticity and non-Gaussian innovations



Note: Fan charts starting in January 2021 for the BVAR with optimally selected Minnesota prior hyperparameters, corrected for the temporary pandemic-related volatility spike during March–May 2020 following Lenza and Primiceri (2022), and allowing for non-Gaussian innovations to accommodate fat-tailed disturbances. The light gray bands denote 68% predictive credible sets. The blue line corresponds to the actual data.

Table 5: Log predictive scores by model, forecast horizon, and variable

Horizon	Model	Spread	Credit growth	ER depreciation	GDP	Inflation	Policy rate
3 months	M1	-27.63	-4.58	-7.66	-27.63	-0.76	-27.63
	M2	-27.63	-10.24	-7.35	-27.63	-0.98	-27.63
	M3	-4.81	-3.71	-3.76	-27.63	-1.70	-4.64
12 months	M1	-3.40	-4.43	-3.76	-27.63	-1.78	-12.38
	M2	-2.68	-7.73	-3.32	-27.63	-1.79	-26.99
	M3	-3.22	-4.82	-4.46	-5.43	-2.76	-3.04
24 months	M1	-2.85	-4.64	-4.29	-10.09	-2.53	-5.74
	M2	-2.63	-7.25	-3.72	-8.23	-2.71	-6.94
	M3	-3.90	-5.31	-4.80	-4.58	-3.16	-3.42
Overall	M1	-7.708	-4.972	-5.586	-17.987	-2.064	-11.802
	M2	-6.720	-8.553	-4.820	-17.255	-2.199	-15.989
	M3	-4.464	-5.007	-4.714	-8.861	-2.804	-4.295

Notes: Log predictive scores (log-scores) for the three Bayesian VAR specifications evaluated at 3-, 12-, and 24-month horizons, as well as the overall average. M1 denotes a Bayesian VAR with optimally selected Minnesota prior hyperparameters under homoskedastic Gaussian innovations. M2 augments M1 by allowing for a temporary volatility spike during March–May 2020, following the heteroskedasticity correction of Lenza and Primiceri (2022). M3 extends M2 by allowing for non-Gaussian innovations and robust inference under higher-order distributional features, following Petrova (2022). The forecasting comparison is intended to evaluate predictive density fit across statistical specifications; it should not be interpreted as a test of the structural identifying restrictions or as independent validation of the economic labeling of shocks. Less negative values indicate better density forecasting performance.

6. Conclusions

This paper studies how the transmission of credit shocks in Peru evolved during the Covid-19 crisis using a Bayesian structural VAR estimated with monthly macro-financial data from 2010 to 2024. The pandemic provides a unique environment to examine credit dynamics, as the period combined an unprecedented contraction in economic activity with large policy interventions aimed at sustaining financial intermediation. The analysis, however, identifies credit supply and credit demand disturbances rather than policy-induced shocks specifically.

From an economic perspective, the results suggest that the transmission of credit shocks changed during the pandemic period. In the pre-pandemic sample, credit supply shocks generate positive but relatively moderate responses in economic activity. Once pandemic observations are included, the response of GDP to credit supply disturbances becomes stronger and more persistent. This pattern indicates that credit conditions may have played a more prominent role in shaping macroeconomic fluctuations during a period characterized by extreme uncertainty and large disruptions to normal economic activity. By contrast, credit demand shocks display weaker and less persistent effects on output and financial variables across subsamples.

At the same time, these results should be interpreted with caution. Although the stronger responses during the pandemic are consistent with mechanisms such as increased reliance on bank credit, heightened uncertainty or the presence of credit-support measures, the empirical framework does not isolate policy-induced shocks from other macroeconomic disturbances. The findings therefore provide evidence on changing credit transmission dynamics rather than a direct evaluation of specific policy interventions.

Methodologically, the paper illustrates how combining sign and zero restrictions with heteroskedasticity adjustments and higher-moment information can help refine structural inference when macro-financial data exhibit volatility spikes and fat-tailed shocks. In the Peruvian data, several reduced-form innovations display excess kurtosis, particularly around the onset of the pandemic. Incorporating this information helps narrow the identified set of impulse responses. However, tighter credible sets should be interpreted as gains in statistical precision conditional on the maintained identifying assumptions, not as independent proof of superior economic identification or as definitive evidence that the structural labeling is uniquely preferred. The forecasting exercise shows that accounting for volatility shifts and non-Gaussian shocks improves density forecasts during turbulent periods. These gains in predictive performance suggest that models that accommodate extreme observations may better capture the statistical properties of macro-financial data during crisis episodes. However, improved forecasting accuracy should not be interpreted as independent validation of the structural interpretation of the shocks. Forecasting performance provides evidence on statistical fit and predictive density accuracy, whereas the economic interpretation of the shocks depends on the maintained identifying restrictions.

Overall, the findings contribute to the empirical literature on credit shocks in emerging economies by documenting how the macroeconomic transmission of credit disturbances can evolve during large systemic disruptions. Future research could explore these dynamics at a more disaggregated level, for example by examining heterogeneity across sectors, industries, or firm sizes, or by studying the interaction between credit shocks and specific policy instruments implemented during crisis periods. Applying the methodology to other emerging economies could also help assess the external validity of the findings.

Declaration of AI use

During the preparation of this manuscript, the authors used Abacus for language editing and grammar improvement. All AI generated outputs were critically reviewed, edited, and approved by the authors, who take full responsibility for the final content of the manuscript.

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Appendix

Appendix A: Minnesota Prior Specification

Let $\beta = \text{vec}(\Phi_1, \dots, \Phi_p, \Phi_0)$ denote the stacked vector of coefficients, and assuming a Gaussian prior

$$\beta \sim \mathcal{N}(\beta_0, \Omega_0), \tag{1}$$

where the Minnesota prior specifies that Ω_0 is diagonal. Following Litterman (1986) and Dieppe et al. (2016), the prior implements three features: (i) overall tightness toward the random-walk baseline; (ii) lag decay (stronger shrinkage for longer lags); and (iii) stronger shrinkage for cross-variable lags relative to own lags via scale adjustment by the residual variances.

For parameters relating variable *i* to its own past at lag *l*, the prior variance is

$$\text{Var}(a_{ii,l}) = \left(\frac{\lambda_1}{l^{\lambda_3}}\right)^2, \tag{2}$$

where λ_1 is the overall tightness parameter and λ_3 controls the rate at which higher-order lags are shrunk toward zero.

For coefficients relating variable i to the lag$-l$ value of variable $j \neq i$, the prior variance is

$$\text{Var}(a_{ij,l}) = \left(\frac{\sigma_i^2}{\sigma_j^2}\right)\left(\frac{\lambda_1}{l^{\lambda_3}}\right)^2, \tag{3}$$

where σ_i^2 and σ_j^2 are the residual variances from univariate AR models for *i* and *j*, and λ_2 is a cross-variable tightness parameter. This cross-variable scaling shrinks coefficients more aggressively when the scale of variable *j* is large relative to variable *i*.

Furthermore, we choose the hyperparameters of the prior to be calibrated to maximize the marginal likelihood, as detailed in Canova (2007) and Giannone et al. (2015).

Appendix B: Identification of Structural Shocks

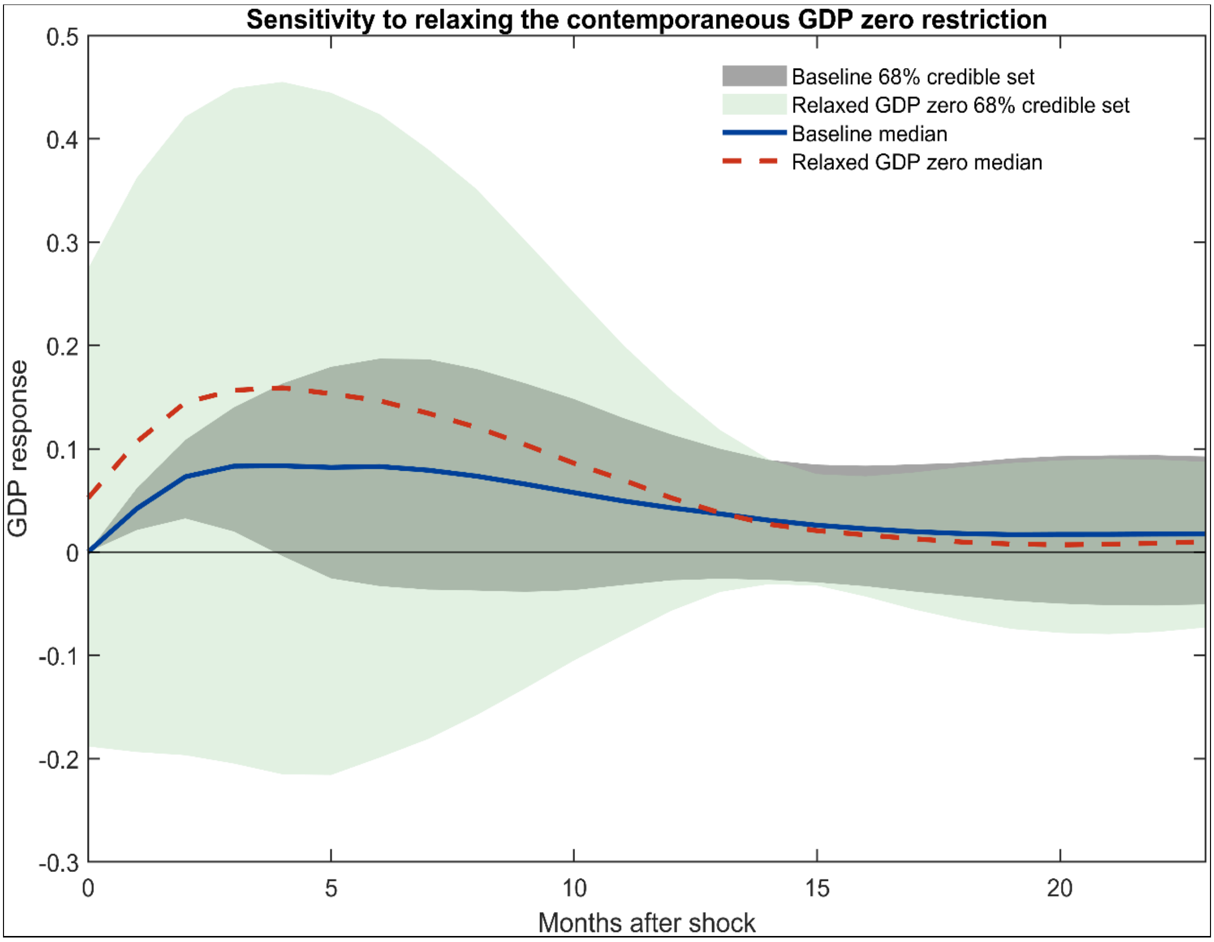
We impose sign and zero restrictions on the rotation matrix Ω following the methodologies proposed by Rubio-Ramírez et al. (2010) and Arias et al. (2018). This approach allows structural shocks to be identified using economically motivated restrictions while remaining agnostic about the exact contemporaneous causal ordering of the variables.

Building on the literature on credit shock identification (e.g., Duchi & Elbourne, 2016; Büyükbaşaran et al., 2022; among others), we distinguish between credit supply and credit demand shocks by exploiting the joint behavior of credit quantities and lending spreads. Credit supply shocks are assumed to move credit volumes and spreads in opposite directions, while credit demand shocks move both variables in the same direction. Additionally, appreciation shocks are assumed to reduce both exchange rate depreciation and inflation simultaneously.

To further refine identification, we impose zero restrictions that rule out contemporaneous effects of financial shocks on GDP. This assumption reflects the idea that financial disturbances affect real activity with short delays due to adjustment frictions in production and investment decisions.

At the same time, this identifying restriction may be more restrictive during crisis episodes, when disruptions in credit markets can transmit rapidly to the real economy. For example, sudden changes in credit supply may immediately affect firms' liquidity conditions, working-capital availability, and production decisions. For this reason, we assess the sensitivity of the results to relaxing the contemporaneous zero restriction on GDP. Appendix Figure B.1 compares the GDP response to a credit supply shock under the baseline identification scheme and under an alternative specification that relaxes this restriction. The qualitative pattern is broadly preserved: the median response remains positive and hump-shaped, although the relaxed specification produces a larger short-horizon response and wider credible sets. This suggests that the contemporaneous zero restriction helps discipline short-run inference, but the positive GDP response is not mechanically generated by imposing a zero contemporaneous effect.

Figure B.1: Sensitivity to relaxing the contemporaneous zero restriction on GDP



Note: The figure compares the GDP impulse response to a credit supply shock under the baseline identification scheme and under an alternative specification that relaxes the contemporaneous zero restriction on GDP for credit shocks. Solid and dashed lines report posterior median responses, while shaded areas denote 68% posterior credible sets. Relaxing the restriction produces a larger short-horizon median response and wider credible sets, but the qualitative pattern remains broadly similar: the GDP response is positive and hump-shaped. The exercise suggests that the contemporaneous zero restriction helps discipline short-run inference, without mechanically generating the positive GDP response to credit supply shocks.

Appendix C: Heteroskedasticity Adjustment

To incorporate the Covid-19 volatility spike into the reduced-form VAR, we follow the heteroskedasticity adjustment proposed by Lenza & Primiceri (2022). This approach allows the innovation variance to shift deterministically during pre-specified high-volatility episodes while leaving the coefficient prior and the Minnesota structure unchanged. Formally, we estimate

$$y_t = \Phi_1 y_{t-1} + \cdots + \Phi_p y_{t-p} + \Phi_0 + s_t u_t, \tag{4}$$

where $u_t \sim (0, \Sigma)$ and s_t is a time-varying scale factor capturing periods of unusually high volatility. Under this specification, the covariance matrix of the reduced-form errors becomes $E(u_t u_t') = s_t^2$, so that heteroskedasticity enters multiplicatively through s_t.

Following Canova & Ferroni (2021), we assume that the Covid-19 uncertainty shock materialized as a short-lived volatility cluster. Accordingly, we set $s_t = 1$ for all t except for the three-month period March–May 2020, during which volatility increases by a factor of ten. This calibrated specification captures the well-documented jump in financial and macroeconomic uncertainty at the onset of the pandemic and corresponds to the heteroskedastic model reported in the empirical results.

Appendix D: Non-Gaussian Identification

The reduced-form errors of the VAR are linked to the structural shocks through

$$u_t = \Sigma^{1/2}\, \Omega\, \nu_t, \tag{5}$$

where $\Sigma^{1/2}$ is the Cholesky factor of the reduced-form covariance matrix, Ω is an orthonormal rotation matrix such that $\Omega\Omega' = I$, and ν_t are structural shocks with zero mean and unit variance. In a Bayesian setting with set identification, Ω is drawn from its uniform distribution on the orthonormal group and retained only if it satisfies a set of economic restrictions (such as sign or zero constraints).

However, sign restrictions alone can produce large identified sets, particularly when innovations exhibit non-Gaussian features. To sharpen identification, we follow Andrade et al. (2023) and impose additional restrictions on the third and fourth moments of the structural shocks. This requires only consistent estimators of asymmetry and excess kurtosis and does not impose a parametric distribution on reduced-form errors. The procedure builds on Petrova (2022), who derive asymptotically valid Bayesian inference for VARs with non-Gaussian innovations using the asymptotic covariance of the QML estimator of the reduced-form parameters.

Appendix E: Identification Algorithm and implementation details

Let $\{\Sigma^{(j)}, \Phi^{(j)}\}$ denote the *j*-th posterior draw of the reduced-form parameters obtained from the corrected posterior distribution in Petrova (2022). For each such draw, structural identification proceeds iteratively as follows.

Algorithm: Bayesian identification under sign, zero, and higher-moment restrictions.

- Draw an orthonormal matrix Ω from the uniform distribution using the Rubio–Ramírez et al. (2010) algorithm.
- Compute the impulse responses implied by Ω and verify that all sign and zero restrictions are˜ satisfied.
- Construct the structural shocks implied by the draw ($\Sigma^{(j)}$,$\Phi^{(j)}$):

$$\widetilde{\nu_t^{(j)}} = \widetilde{\Omega'}\left(\Sigma^{(j)}\right)^{-1/2}\left(y_t - \Phi_1^{(j)} y_{t-1} - \cdots - \Phi_p^{(j)} y_{t-p} - \Phi_0^{(j)}\right). \tag{6}$$

- Compute the shrinkage estimators of skewness and kurtosis, $\mathcal{S}\left(\widetilde{\nu_{n,t}^{(j)}}\right)$ and $\mathcal{K}\left(\widetilde{\nu_{n,t}^{(j)}}\right)$, as in Petrova (2022), Andrade et al. (2023).
- Check whether the higher-order moment inequalities imposed on the target structural shock are satisfied.
- If both the economic (sign/zero) and moment restrictions hold, retain the draw by setting $\Omega^{(j)} = \Omega$; otherwise, discard˜ Ω and repeat the procedure.

- Continue until a sufficiently large number of accepted draws is obtained to approximate the posterior distribution of the impulse responses.

The robust Bayesian estimation follows the empirical steps described in Canova & Ferroni (2021). The VAR is estimated with p = 6 lags. Lag selection was guided by the Akaike information criterion (AIC), the Hannan–Quinn information criterion (HQIC), the Bayesian information criterion (BIC), and the log marginal likelihood of the reduced-form VAR. We compared the statistical fit for $p \in \{3,6,12\}$ using the full sample (results available upon request). While p = 12 achieves the best information criterion values, the improvement relative to p = 6 is modest and comes at the cost of a substantial increase in parameters for a monthly VAR with six variables. Following Canova (2007) and Giannone et al. (2015), we adopt p = 6 as it provides a good compromise between dynamic richness and Bayesian shrinkage. It yields a sufficiently flexible moving-average representation for structural analysis without the numerical instability and overfitting risk associated with very high lag orders. Results for the p = 3 specification, available upon request, lead to the same qualitative conclusions.

Posterior simulation is based on 20,000 draws from the reduced-form posterior, discarding the first 5,000 draws as burn-in. Structural identification proceeds by sampling orthonormal matrices Ω using the algorithm of Rubio-Ramírez et al. (2010). Each rotation is retained only if it satisfies (i) the imposed sign and zero restrictions and (ii) the higher-moment inequalities on asymmetry and excess kurtosis following Andrade et al. (2023). The accepted rotations form the posterior distribution of impulse responses under robust Bayesian inference. All estimation and identification procedures are implemented using the BVAR toolbox of Canova & Ferroni (2021), which supports posterior sampling, sign and zero restrictions, heteroskedasticity adjustments, and identification under non-Gaussian innovations.