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The Impacts of Credit Availability: An Impulse Response Function analysis

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Abstract

This paper employs Local Projections (LPs) to analyse the impact of the Flexible Credit Line (FCL), an International Monetary Fund (IMF) initiative introduced during the Global Financial Crisis (GFC). LPs offer insights into the responses of macroeconomic variables following access to the FCL. It focuses on GDP and other economic indicators in Chile, Colombia, Mexico, Peru and Poland. Notably, GDP responses exhibit cyclical patterns, with little immediate impact but discernible effects during economic fluctuations. Examination of current, capital, and financial accounts reveals varied and imbalanced responses. Overall, the study suggests that the FCL's impact is more pronounced during economic imbalances.

Keywords: Local Projections, Impulse Response Function, International Monetary Fund, Flexible Credit Line

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1. Introduction

Impulse Response Functions (IRFs) are employed when one wants to see the effect that a shock has on other variables. IRFs simulate how a specific variable behaves over time after a shock has occurred. When computing IRFs, the most common method to get the IRF coefficient is to fit a Vector Autoregressive (VAR) model to the data and then calculate the responses of the variables. Local Projections (LPs) are a relatively new method that has been used in order to get the IRF coefficients (Jordà et al., 2005) and that brings together both macro and micro econometricians[1]. In this paper, I make use of LPs in order to analyse the effects that the Flexible Credit Line (FCL) had on some relevant macroeconomic variables, such as Gross Domestic Product (GDP), Current, Capital and Financial Accounts and Unemployment Rate. The FCL is a line of credit created by the International Monetary Fund (IMF) amid the Global Financial Crisis (GFC) to mitigate the effects of the recession. In order to gain access to this line of credit, countries have to have sound economic and financial foundations and have to respect certain criteria to be deemed trustworthy and reliable. The FCL case sparked discussions since the majority of the countries' macroeconomic conditions ameliorated just by having access to the IMF funds, and not withdrawing from them. For other countries this did not happen, and they had to withdraw from the IMF funds in order to safeguard their economic wellbeing. In the following, we explore the responses of macroeconomic attributes after gaining access to the line of credit.

Section 2 reviews the literature upon which LPs are based on and subsequent academic papers that build on it in order to make policy evaluations. Section 3 thoroughly describes the data and the ways in which it was transformed to model the shocks and builds on the methodology behind the econometric approach. Section 4 describes the results that were obtained using LPs to

[1] In the microeconometrics field, LPs can be employed when the researcher wants to see the effects that a treatment had on the treated group compared to the control one.

compute IRFs, while Section 5 provides some concluding remarks. Lastly, Section 6 focuses on the limitations of this approach and on what future research in this field could focus on.

2. Literature Review

LPs are simple linear regressions of a future outcome on current covariates (Jordà et al., 2005). The projections simply compare the conditional mean of a future outcome subject to an intervention, and the conditional mean of another outcome not subject to that intervention (Jordà 2023). In this sense, we can see the way in which LPs unite both macro and micro econometrics. In the macroeconometrics framework, we can think of a comparison of two different forecasts under different contexts. While for microeconometrics the experiments realm comes to mind with the effect that a treatment has on the participants and the control group. Since LP estimators are regression coefficients, their interpretation is simpler and more intuitive than coefficients estimated from VAR models (Montiel Olea and Plagborg-Møller 2021). By using LPs, we can compute IRFs without specifying and estimating the underlying multivariate dynamic system (Jordà et al., 2005). VAR models extrapolate impulses from distant horizons, but instead, our approach estimates LPs at each period of interest. Using the LPs method has several benefits when it comes to estimation. In specific,

i. these regressions can be estimated by simple least squares and, therefore, the analysis can be carried out with standard regression packages;
ii. LPs are robust to misspecification of the Data Generating Process (DGP), with misspecification we would have biased coefficients and error terms, and thus, biased parameter estimations;
iii. joint or point-wise analytic inference is simple[2];

[2] Joint inference refers to the simultaneous test of different hypothesis, e.g. joint significance with an F-test of regression coefficients. Point-wise inference, instead, focuses on individual parameters and consists of hypothesis testing or constructing confidence intervals for some parameter.

iv. lastly, this econometric approach allows for experimentation with non-linear methods and more flexible specifications that are otherwise avoided in multivariate settings.

When VAR models are misspecified, the impulse responses that are built from the underlying data are likely to be biased. This happens because "an impulse response is a function of forecasts at increasingly distant horizons" (Jordà et al., 2005) p. 162, and therefore, errors that come from the misspecification of the model are compounded with the forecasting errors, which increase as the forecast horizon increases. The LPs approach is based on sequential regressions of the endogenous variable moved some steps ahead, a procedure that resembles that of multi-step forecasting. One can think that, since the LPs approach does not pose any particular restriction, it would be far less efficient than VAR models, which are known for imposing many restrictions and orderings. This issue of efficiency loss can be greatly reduced once one takes into account lags of the variables as controls (lag-augmented LPs) (Montiel Olea & Plagborg-Møller, 2021; Breitung & Brüggemann, 2023; Dufour et al., 2006). Macroeconomic data is known to be persistent, and that is why lag-augmented LPs significantly help with persistent data. Moreover, lag-augmentation also simplifies the computation of standard errors (SEs), an issue which will be discussed more in depth in Section 3. Montiel Olea & Plagborg-Møller (2021), p. 1790, also prove that, with lag-augmentation, "confidence intervals have correct asymptotic coverage uniformly over the persistence in the DGP and over a wide range of horizons". That is, even if the data is non-stationary (has a unit root) and taking into consideration h horizons, that can grow with the sample T, confidence intervals remain valid (Inoue and Kilian 2002; Montiel Olea and Plagborg-Møller 2019).

Equiza-Goñi and Perez de Gracia (2019) analyse the effect that state-dependent oil prices have on US stock returns using LPs. They employ this approach because of the abovementioned reasons, which make LPs an effective and simpler way to estimate impulse responses, particularly in the case in which the underlying DGP is unknown and there are risks of misspecification. Similarly, Abbritti et al. (2020) make use of LPs to assess the magnitude of the impacts that oil price shocks have on the US economic activity. Precisely, they exploit the flexibility of LPs and introduce non-linearities when computing the impulse responses. LPs were also used to deepen the understanding of the Brazilian Central Bank (BCB) concerning what method to use to control inflation rates in the country. In fact, in this study, IRFs computed by LPs were plotted in the same charts as IRFs produced by more conventional VAR models and it clearly shows that IRFs computed from LPs can better accommodate for non-linearities in the data (Carcel, Gil-Alana, and Wanke 2018). LPs are a useful alternative to VAR models when the objective is to generate IRFs, while taking into account all of the potential misspecification issues that could arise if the model was indeed misspecified.

3. Data and Methodology

The countries considered to perform the analysis in this work project are the countries that, after a thorough assessment by the IMF Staff, have been accepted into the FCL. These countries are Chile, Colombia, Mexico, Morocco, Peru and Poland. Morocco was excluded from the analysis since data availability for this country is scarce and, for reasons detailed below, we decided to omit it. When a country accesses the FCL, it has the right to withdraw a predetermined percentage of its quota towards the funding of the IMF. The money that the country eventually borrows has to be repaid, with interest, to the IMF. The IMF is known for its *ex-post* conditionality clauses[3], that, given the soundness of the countries accepted into the FCL is not present for this funding program (Flexible Credit Line (FCL), IMF Staff, 2023). More specifically, the IMF Staff, before admitting any country into the line of credit, performs a thorough investigation into the macroeconomic and legal foundations of the state.

[3] Conditionality refers to the practice of asking a country to adjust the very policies that led the country to ask the Fund for help, (IMF Conditionality, IMF Staff, 2023).

If the country's institutions receive positive feedback, the nation is then admitted into the FCL. This check, that the IMF Staff performs beforehand, ensures the institution that the country is deemed financially stable enough to repay the money that it will eventually withdraw from the Fund. By following this procedure, the FCL has no conditionality clause attached to it.

All of the data used to perform this analysis is taken from the IMF Database. Some variables have gaps in certain years but, in order to have consistency of measurement across the data, we chose not to look in other databases. Quarterly data was collected in order to have a more granular view of the variables. The sample size varies from country to country, based on data availability, but the individual samples span as follows:

Chile	**Colombia**	**Mexico**	**Peru**	**Poland**
1996Q1 - 2023Q2	2005Q1 - 2023Q2	1993Q1 - 2023Q2	2007Q1 - 2023Q2	1995Q1 - 2023Q2

The variables taken into account to perform the analysis are the following:

i. Gross Domestic Product (GDP) in nominal terms, measuring economic production. It considers current prices in the calculations, not adjusting for inflation.
ii. Current Account, measuring the country's transactions vis a vis the rest of the world.
iii. Capital Account, which shows capital transfers receivable and payable between residents and non-residents and the acquisition and disposal of non-produced, nonfinancial assets between residents and non-residents (International Monetary Fund 2009).
iv. Financial Account, using the IMF's definition, is a component of a country's Balance of Payments (BoP)[4], includes direct investment, portfolio investment and reserve assets.

[4] The BoP includes the Current and the Financial accounts, as per IMF definition of these accounts (International Monetary Fund 2009).

v. Unemployment Rate, quantifying the percentage of people in the labour force who are unemployed.

vi. The amount of money approved under the FCL, in Special Drawing Rights (SDR)[5].

Regarding data availability, for Colombia there was no record for Capital Account figures, so this variable has been omitted for the Colombian case.

In the IMF Database, GDP was measured in the domestic currency of the country, while the accounts were measured in US dollars. In this Section we specify how we dealt with the different units of measurement of the data.

The statistical software employed in the analysis is Stata 18, that contains a new package that deals with LPs and the deriving of IRFs (Stata 18 2023a).

After performing an augmented Dickey-Fuller test for non-stationarity[6] on all variables, the results indicate that GDP is non-stationary. Therefore, the best approach was to calculate the quarter-on-quarter growth rate of the variable. Jordà (2023) states that LPs can be estimated on the first differences of variables, and on growth rates, obviously paying attention to the fact that transforming the variable also means changing its interpretation. We take this into consideration when examining the results of the analysis in Section 4. It is worth noticing that, in the economic literature, the level of GDP is considered to be integrated of order one $I(1)$, and when calculating the growth rate, using first differences of logged GDP, we are making the variable stationary. Lastly, the growth rate of GDP was also taken because the amount was denominated in domestic currency. Therefore, with the new transformation, we can easily compare results across countries without worrying about converting the currencies.

[5] The SDR is an international reserve asset, its value is based on the US dollar, the euro, the Chinese renminbi, the Japanese yen and the British pound sterling.

[6] The Dickey-Fuller test was performed on the variable with a trend component and a number of appropriate lags, as suggested by the Bayesian Information Criteria (BIC).

A further transformation that was made to the data was taking the growth rate of the Capital, Current and Financial Accounts, as well as the amount of SDR approved under the FCL. This way, when analysing the results, we can have comparable figures. Since these variables were denominated in US dollars, this would have made the interpretation impossible, in this way we can have a comparable sample for our analysis despite the different currencies that the variables were denominated in.

For what concerns the methodology, we use LPs to calculate the impulse responses of our variables. Let us start by giving the mathematical definition of impulse response and build from there. Specifically, an impulse response can be defined as the difference between two forecasts, i.e.,

$$IR(t, s, d_i) = E(y_{t+s}|v_t = d_i; X_t) - E(y_{t+s}|v_t = 0; X_t) \qquad s = 0, 1, 2, \ldots \tag{1}$$

More specifically, in (1), $E(.\,|.)$ expresses the expected value conditional on the occurrence of some shock, or, in other words, the best mean squared prediction error. v_t is the n x 1 vector of reduced-form[7] residuals, while D is a n x n matrix, and its columns d_i have the experimental shocks. y_t is a random vector of dimensions n x 1, and $X_t \equiv (y_{t-1}, y_{t-2}, \ldots)$. Thus, the objective of this expression is to generate the best mean-squared multi-step predictions. This is precisely the instance in which LPs come into play. In the literature, the most widely used model to calculate IRFs is the VAR model. However, as explained in Section 2, if the model does not represent the DGP[8] adequately, the coefficients of the impulse responses generated from it are likely to be biased. One way to get around this problem is to use a model that is re-estimated at each forecast horizon considered, a procedure called direct forecasting (Jordà et al., 2005).

[7] A model expressed in reduced from represents the endogenous variables as a function of the exogenous and predetermined ones. This way of writing the model clearly highlights the relationship between reduced form coefficients and structural coefficients as well as between structural disturbances and reduced form disturbances.
[8] That is, the VAR model is misspecified and it therefore projects the misspecification into its estimates.

We therefore project y_{t+s} in the linear space created by $(y_{t-1}, y_{t-2}, \dots, y_{t-p})'$. More specifically, the model is,

$$y_{t+s} = \alpha^s + B_1^{s+1} y_{t-1} + B_2^{s+1} y_{t-2} + \cdots + B_p^{s+1} y_{t-p} + u_{t+s}^s \qquad s = 0, 1, 2, \dots, h \tag{2}$$

where α^s is a vector of constants of dimension n x 1, B_i^{s+1} is the parameter matrix associated to lag i at horizon s + 1. Jordà et al. (2005) define the collection of the h regressions as *local projections.*

In this instance, we can return to (1) and rewrite it as,

$$\widehat{IR}(t, s, d_i) = \hat{B}_1^s d_i \qquad s = 0, 1, 2, \dots, h. \tag{3}$$

It is important to notice that in equation (3), $\hat{B}_1^s$ represent the impulse response coefficients, while the resulting residuals, u_{t+s}^s in equation (2) are a moving average of the forecast errors from time t to $t + s$, and thus, uncorrelated with the regressors which are dated $t - 1$ to $t - p$. Jordà et al. (2005) have an extensive section in their paper which exemplifies the derivation cited above.

However, even if the residuals are not correlated with the regressors, Montiel Olea & Plagborg-Møller (2021) show that they are serially correlated, even if the error is independent and identically distributed (i.i.d)[9]. If we look at equation (3), we can observe that

$$u_{t+s}^s \equiv \sum_{h=1}^{s} B_1^s \, \varepsilon_{t+h} \tag{4}$$

It is straightforward to see that the regression residuals are serially correlated, i.e. they are autocorrelated, not independent from one another.

[9] Derived from the Gauss-Markov theorem, innovations have expected value of 0, constant variance and are uncorrelated.

The approach that Montiel Olea & Plagborg-Møller (2021) use to robustify the results obtained from LPs is *lag-augmentation.* Lag-augmentation basically consists of using a lag of the dependent variable as control variable. With this additional specification in the model, we further ensure that conventional results hold[10]. In order to choose the optimal number of lags, we use the Bayesian Information Criteria (BIC), a method largely used for model selection. When choosing the number of lags, we want to be conservative and that is precisely the reason why we employ the BIC instead of the Akaike Information Criteria (AIC), which is known to be less conservative. Nonetheless, using the right amount of lags is not central to producing consistent LPs estimates. Montiel Olea & Plagborg-Møller (2021) show that as long as enough control variables are included in the model, regressors will satisfy the conditional mean independence condition.

Delving into the topic of SEs, in the paper by Jordà et al. (2005), the authors recommend the use of heteroskedasticity and autocorrelation robust (HAC) SEs in order to obviate the serial correlation of regression residuals. Montiel Olea & Plagborg-Møller (2021) demonstrate that, by using lag-augmented LPs, this additional specification while running the regression is not needed, and instead, the generally used Eicker-Huber-White heteroskedasticity-robust estimator is sufficient. This procedure widely simplifies the computation of SEs since we do not have to specify the HAC procedure or choose bandwidths. It is known that using lags of the dependent variable, i.e. lag-augmenting a model, improves inference in autoregressive specifications (Dolado and Lütkepohl 1996; Toda & Yamamoto, 1995). Therefore, in this analysis we use a lag-augmented LPs model and then select a heteroskedasticity robust estimator in order to have consistent estimates across our study. Other approaches have been explored, such as a parametric wild bootstrap procedure (Montiel Olea and Plagborg-Møller

[10] This specification is an additional safeguard to make sure that the variables used in the analysis are stationary, but it is not necessary in our case, since we use the growth rates of said variables.

2021) or using a parametric specification of the residual covariance matrix (Jordà, 2023; Lusompa, 2021).

The local projection that we estimate is therefore computed from,

$$y_{t+s} = \alpha^s + \beta_s s_t + \gamma_s X_t + u_{t+s} \qquad s = 0, 1, 2, \dots, h \qquad (5)$$

where X_t is a vector containing all variables previously specified in this Section. The identification of this equation will be consistent if the variation in s_t is exogenous given X_t (Jordà, 2023).

Lastly, it is also worth noticing that, depending on the lag length and the dimension of y_t, there will be degrees of freedom constraints for small samples, like the one taken into consideration in this analysis. Nevertheless, these are problems with which Stata 18 and the LPs command can deal with (Stata 18 2023b). More specifically, the small sample degrees of freedom adjustment comes into play when the residual covariance matrix is computed. When specifying this option, Stata uses $1/_{T - m}$ instead of using the large sample divisor $1/_T$. In this formula, m is the number of independent variables used to compute the LPs. Additionally, the small sample specification prompts the software to show the small sample t-statistics instead of the usual large sample statistics.

4. Results

An IRF can also be defined as the impact of a transitory shock ε_t on present and future values of y_t, and therefore be represented as

$$\frac{\delta y_{t+n}}{\delta \varepsilon_t} = \Psi_n \qquad n = 1, 2, 3, \dots \qquad (6)$$

Beyond the IRFs, Stata also showcases the confidence intervals for the parameters estimated, which are computed as,

$$\left[\hat{\theta} - z_{1-\alpha/2}\widehat{se},\ \hat{\theta} + z_{1-\alpha/2}\widehat{se}\right]. \tag{7}$$

In this Section, we will examine the results of the LPs and IRFs. We will go through the responses of our variables, given a shock in the FCL variable. In the Appendix, the IRFs charts for the other shocks can also be found. Since this research spans through five different countries, the clearer way to present the results is one variable at a time. Starting with GDP and continuing with the accounts and concluding with the unemployment rate. This way, we can see the heterogeneity or homogeneity of the responses of the variables to the impulses across different states. The countries' results will be presented in alphabetical order.

4.1 Gross Domestic Product

A shock in the FCL variable ultimately means a new renewal of the contract between the country and the Fund. Therefore, we are analysing what impact an unexpected renewal of this contract would have on the country's overall economy. For what concerns GDP, we can see some heterogeneity in the responses of the countries in the sample. The cyclicality of GDP can be observed better in Chile and Poland (Figure 1 and Figure 5). Moreover, it can also be observed that the impulse response hoovers around the steady state, i.e. close to no change (Figure 2). The cyclical component of GDP is clearly shown in Figures 1 and 5 and reflects the cyclicality of economic development. This is indicative of the fact that a new approval of credit by the IMF does not necessarily boost the economy, it seems to give confidence to people that, in case of need, the funds will be withdrawn to avoid or dampen the effect of a potential crisis. The Chilean GDP's reaction to an FCL shock can be considered, as already mentioned, highly cyclical. Periods of decrease of GDP are followed by periods of higher growth, with a continuing repetition. When studying the end of the forecast horizon we notice a larger decline in the country's GDP, maybe due to higher uncertainty. Analysing the Colombian case, we see a peak in GDP towards the 7th quarter of the IRF, followed by the start of a declining pattern towards the end of the horizon. Regarding Mexico, GDP seems to be fluctuating around 0 percent change, but in the first and last horizons, we see some minor shocks. These imbalances are quickly followed by an impressive recovery of GDP, which has an unprecedented increase. In the longer-term, it seems to suffer another shock, which is surrounded by higher degrees of uncertainty, as depicted by the size of the confidence intervals. Peru's GDP seems to follow the cyclical trend that we have seen in Chile and Poland. However, it can also be noticed in Figure 4 that a sharp increase of GDP happens in the 9th quarter, towards the end of the forecast horizon. This period of growth, nonetheless, is short-lived, as it seems that in the 10th quarter the IRF values decrease again. Poland's GDP seems to express the high cyclicality of the economy (Figure 5). Towards the end of our scenario, we observe a somewhat sharp contraction in the IRF, which also comes with higher statistical uncertainty. Notwithstanding the cyclical component of GDP, we can also observe that the FCL shock on GDP is not persistent in any country. This most likely reflects the essence of the line of credit: a mere possibility to withdraw from it in case of need. Basic economic reasoning would argue that, as people have access to more credit, they will spend more and this, in turn would increase their country's GDP. However, the FCL is all about the possibility of withdrawing funds, and not some immediate growth in citizens' disposable income. In this context, the larger availability of credit does not significantly alter the economic conditions of the countries involved. However, it provides a safety net for the recipients of the FCL, an added degree of safety from eventual macroeconomic imbalances.

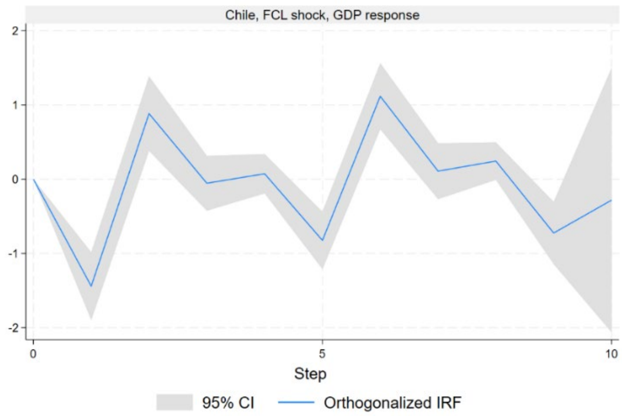

Figure 1, effect of a FCL shock on GDP in Chile

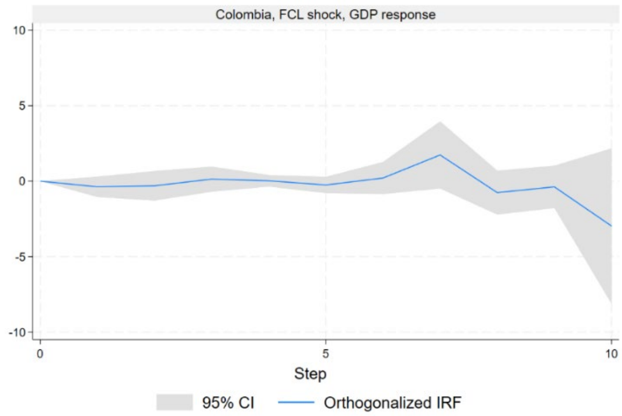

Figure 2, effect of a FCL shock on GDP in Colombia

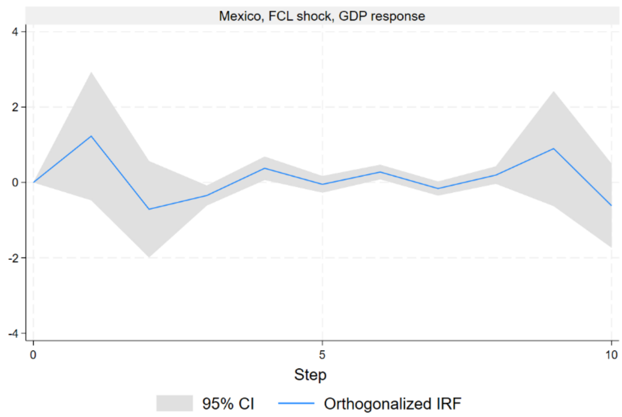

Figure 3, effect of a FCL shock on GDP in Mexico

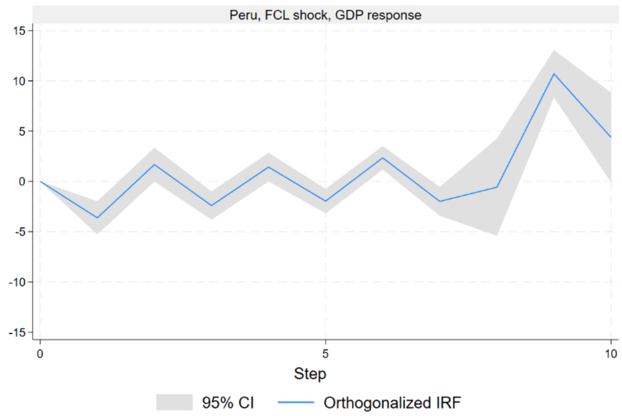

Figure 4, effect of a FCL shock on GDP in Peru

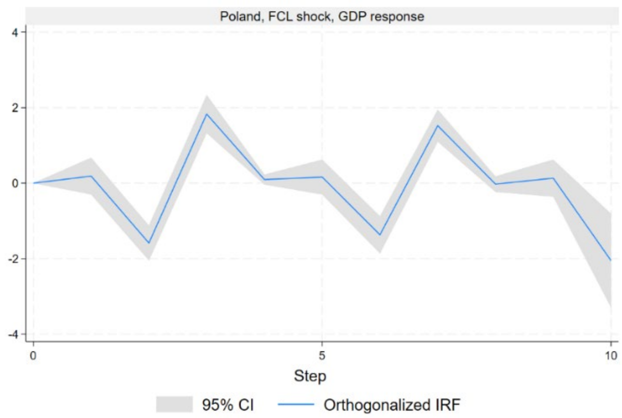

Figure 5, effect of a FCL shock on GDP in Poland

4.2 Current, Capital and Financial Accounts

It is important to notice that the quarterly data for the Current, Capital and Financial accounts is extremely volatile for these countries. This is of course reflected in the LPs and the subsequent IRFs, which show very large magnitudes, despite using the growth rates of the variables. We can argue that these imbalances were a part of the reason why the countries applied to be a part of the line of credit in the first place, so we expect them to be very volatile and have larger confidence intervals. For what concerns the Accounts, we can argue that as credit increases in a certain country, this might attract foreign investment, as well as cause a rise in imports or a soar of financial transactions. However, as discussed in the following, we do not notice any major shifts in the Accounts, as the countries did not withdraw from the Fund, but only entered into the FCL. For what concerns Chile, we can see somewhat the same behaviour in the Capital and Financial Accounts, following an FCL shock. After news break of this new agreement, both the country's investment and transaction see an upward shock, aided by the confidence that the availability of credit gives to citizens (Figure 6). Looking at the Current Account, so the variable that determines whether the country is a net creditor or lender, we cannot come to the same conclusions. The Account seems to fluctuate around the steady state, suffering a steady decrease from the 5th quarter onwards (Figure 7). Analysing Figure 8, the response of the Colombian economy, we can argue that the Current and the Financial Accounts follow closely the same behaviour. They both see first an increase, followed by a slow descent towards the steady state, ultimately meaning no change in the variables in the longer term. Moving to Mexico, Figures 9 and 10 depict the Accounts' responses, and we see that all three accounts have basically no reaction to the line of credit, but with different magnitudes. While the reactions of the Capital and Current Accounts are more contained, we see that the Financial Account's response is larger. This can be due to the large imbalances that were recorded in the Mexican Financial Account immediately after the Global Financial Crisis (GFC) and the subsequent years after that. Focusing on Peru, Figures 11 and 12 help us understand the behaviour of the economy following the shock. The Current Account has a small response to the FCL shock, while the Financial one seems to be more reactive, with several downward shocks followed by short-lived recoveries. The Capital Account, on the other hand, suffers from some hiccups in the first quarters of our forecast horizon, but stabilizes around 0 after the turbulences. In Poland (Figure 13) the Capital Account showcases no reaction after an FCL shock, while the Current and Financial Accounts exhibit first no reactions and then suffer from shocks in the 7th and 8th quarters respectively. The same economic reasoning that was applied to GDP's response to a FCL shock can be applied to the Accounts as well. The shock can be deemed as transitory as we do not see any permanent alterations to these variables in the long-run. We can observe the variables' responses to the shock in the very short-run and then some other shocks in the longer-run, but no shock seems to permanently alter these three variables. In this particular case, the large fluctuations are due to the great BoP imbalances that these countries suffer from. Nonetheless, in this context, the FCL proved not to have a positive effect on the growth rate of these variables. That is, the availability of additional credit to the countries did not contribute to macroeconomic wellbeing, but it contributed to the stability of the economies. In this case, Colombia can be considered an exception because, looking at Figure 8, we can see that both the Current and Financial Accounts benefitted from the augmented credit availability. Namely, both the Accounts notice an increase of around 8%. Of course, this result does not come without fluctuations and larger shocks, but it is proof of the power of credit availability for some specific economies.

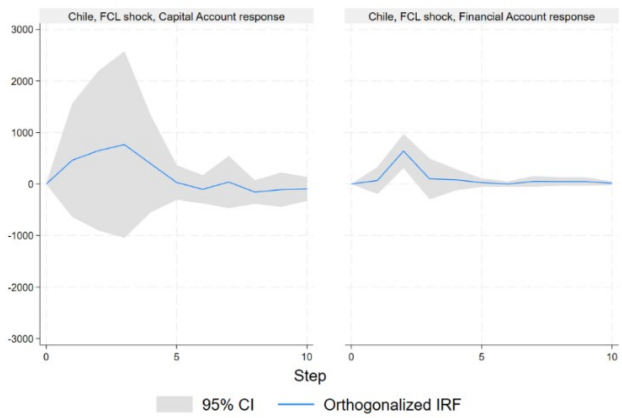

Figure 6, effect of a FCL shock on the Capital and Financial Account in Chile

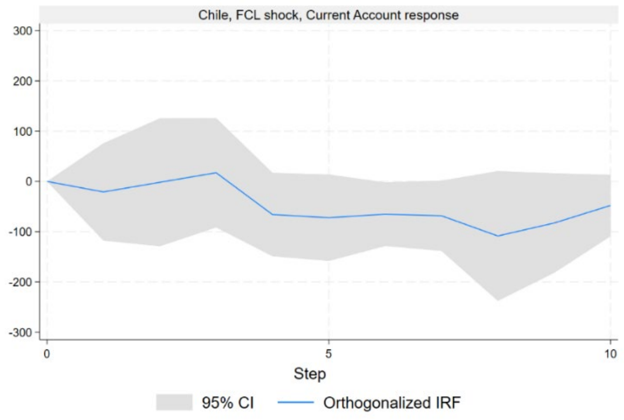

Figure 7, effect of a FCL shock on the Current Account in Chile

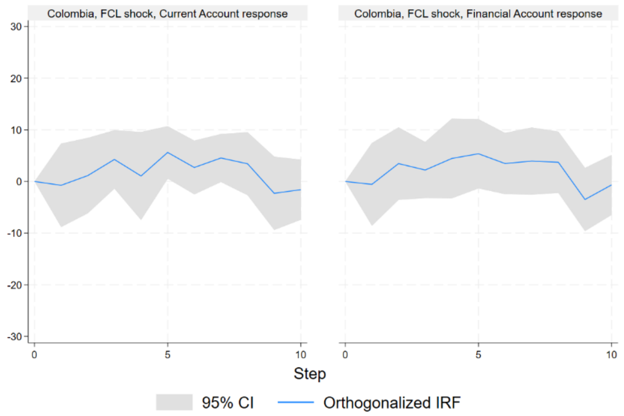

Figure 8, effect of a FCL shock on the Current and Financial Account in Colombia

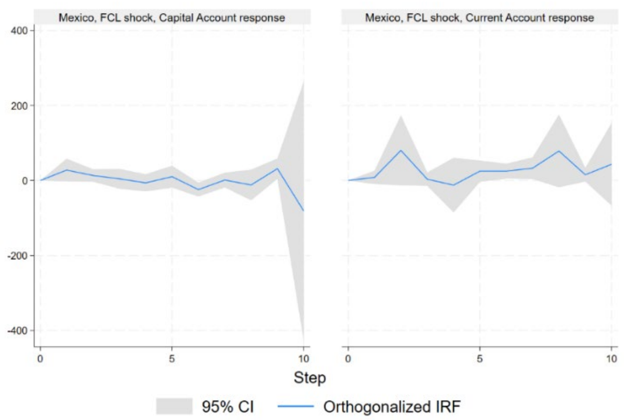

Figure 9, effect of a FCL shock on the Capital and Current Account in Mexico

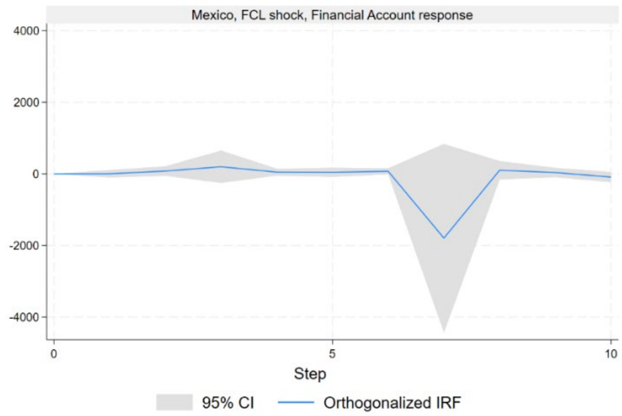

Figure 10, effect of a FCL shock on the Financial Account in Mexico

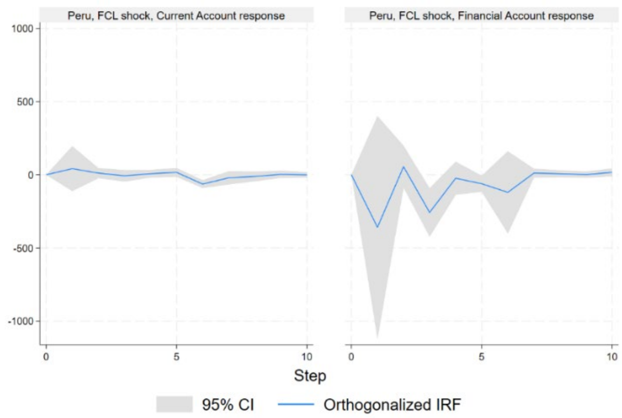

Figure 11, effect of a FCL shock on the Current and Financial Account in Peru

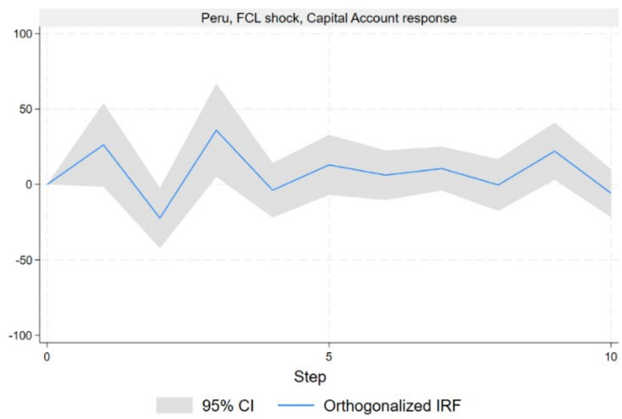

Figure 12, effect of a FCL shock on the Capital Account in Peru

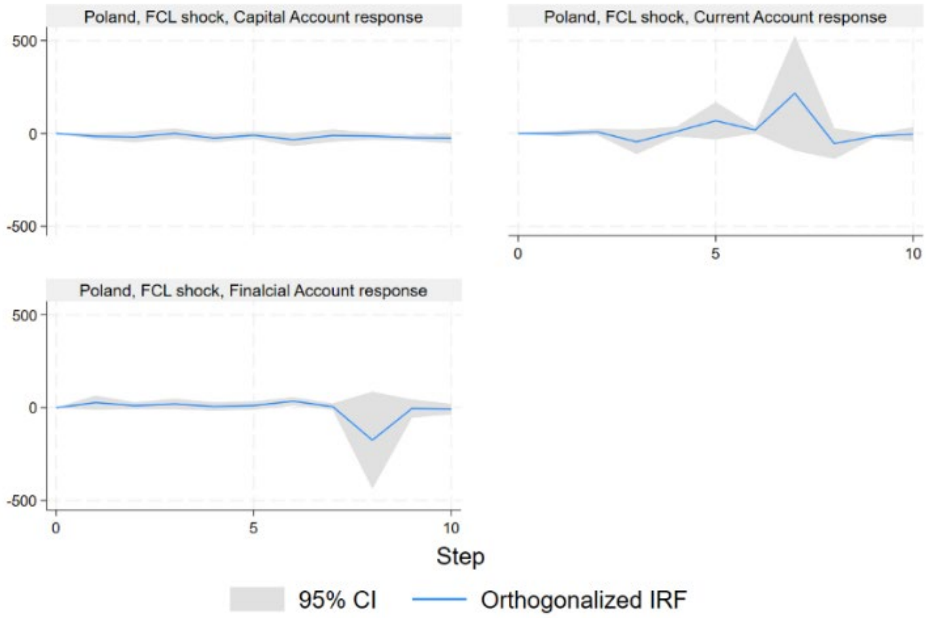

Figure 13, effect of a FCL shock on the Capital, Current and Financial Account in Poland

4.3 Unemployment Rate

Figures 14 through 18 depict the behaviour of the unemployment rate after a temporary shock ε_t was simulated on the credit line. For this variable, we can see that the response of the five countries is very homogeneous. First, the impulse response is stable around 0, but after some quarters, we observe a steady increase of the unemployment rate. More specifically, in Chile we see a sharp increase of about 0.8% in unemployment rate, after the 5th quarter, followed by what seems like a steady decline towards zero (Figure 14). On the other hand, in Colombia the unemployment rate hovers around zero, with some upward and downward shocks of small magnitude, depicted in Figure 15. The unemployment rate's response in Mexico, Peru and Poland can be compared to the Chilean's response. The peak of the unemployment rate appears respectively at the 8th, 7th and 10th quarter after the initial shock (Figures 16 through 18). After this hike, in Chile, Mexico and Peru, we can see a slow decline of the variable. In the Appendix (Section 8.1), we can see that in Poland, for which we have a 40-quarters horizon, the unemployment rate is slowly decreasing to its initial value. This common behaviour of the variable could represent the confidence that being part of the FCL gives. It is strong for the first quarters but fades with the passing of time. After a new contract is signed under the FCL the rate of employment stays flat, signalling that the economy has found a safety net. However, after this confidence fades, we see an increase in unemployment, probably due to the slowdown of the overall economy, caused by a loss in confidence. In this context, it is also important to point out the delay with which firms respond to these types of shocks. Their response is not immediate, as it takes time for them to assess the current economic climate. In this respect, we can clearly see this delay in the Unemployment Rate adjustment as its response is lagged in all countries taken into consideration in the analysis. In the same way, Unemployment Rate can be considered as very persistent, for the reasons cited above, and this is shown in the persistence of the FCL shock in this variable. The shock hits the Unemployment Rate with some quarters of delay, but when it does its response is persistent. Employers do not react immediately to the shock and, when the shock is gone, cannot adjust in a timely manner as well. This is a reflection of the slowness of the labour market, which always has a lagged response to economic shocks.

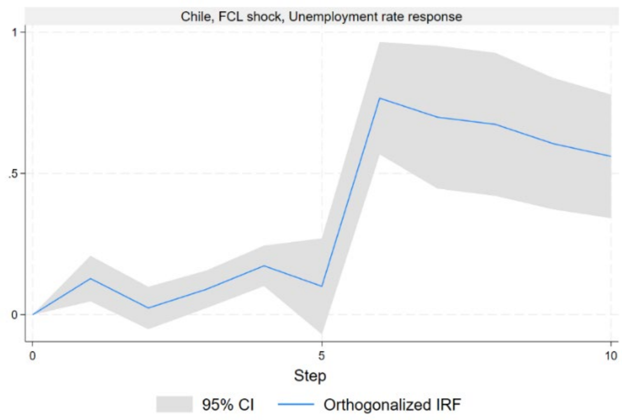

Figure 14, effect of a FCL shock on the Unemployment Rate in Chile

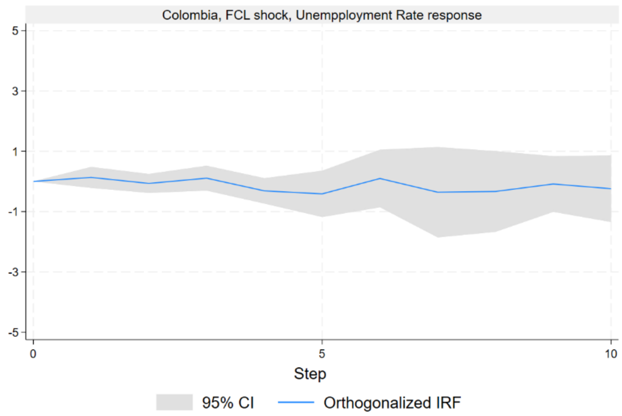

Figure 15, effect of a FCL shock on the Unemployment Rate in Colombia

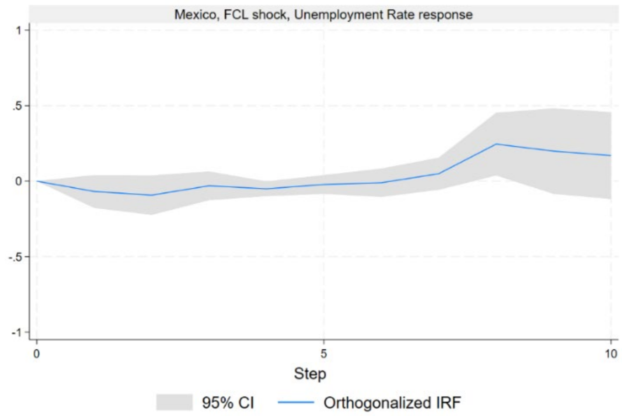

Figure 16, effect of a FCL shock on the Unemployment Rate in Mexico

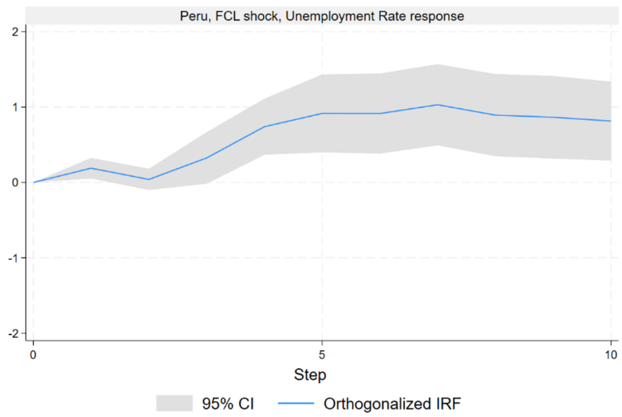

Figure 17, effect of a FCL shock on the Unemployment Rate in Peru

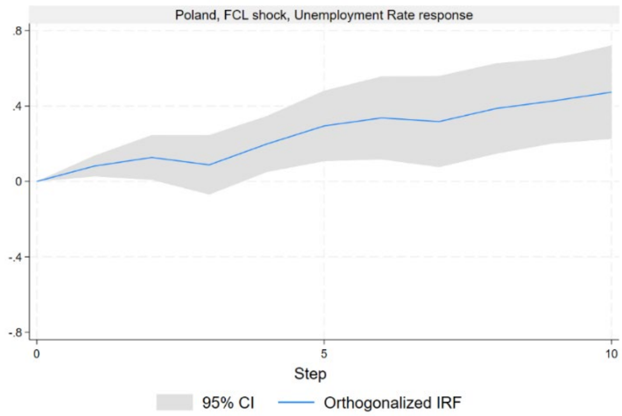

Figure 18, effect of a FCL shock on the Unemployment Rate in Poland

5. Conclusion

Throughout Section 4, we can observe that, for most IRFs, the impact of the FCL shock was not immediate. This is due to the fact that people did not react immediately to the shock since theoretically, nothing changed in their mind and pockets. The FCL shock just reiterates the availability of credit in case of need. The fact that we see barely any reactions from this shock is because people did not have a surplus of credit to finance themselves. Overall, looking at the presented results, we can conclude that in "normal" periods the Flexible Credit Line's effect on the economy is irrelevant. However, when there are either upturns or downturns in the economic climate, we see that the FCL has a more substantive impact on the variables. This impact comes some periods after the initial shock because of the population's delayed responses to the shock. For what concerns policy implications, it can be argued that if a country enters the FCL expecting enhanced economic activity just by being a member, this is clearly not the case. In order to fully benefit from it, the recipient has to withdraw from the line of credit. Only in this way the national economy will see positive and persistent effects. All in all, we can state that the larger availability of credit did not help immensely ameliorate these countries' macroeconomic positions. However, we can argue that it played an important role in stabilizing and giving confidence to sluggish and stagnant economies.

6. Limitations and Further Research

For what concerns the limitations that stem from this analysis, the most concerning one is the sample size. For some countries it can be noticed that the IRF horizon is significantly smaller than others. During the estimation of LPs, the range of the estimation had to be decreased in order for the software to actually perform the calculations. This can be limiting the analysis since, with a limited time horizon, we can only see short-term developments of the variables taken into consideration. Therefore, our understanding of the long-term effect that the shock has is limited in this sense.

Further research could focus on increasing the sample size, even turning to monthly data, to achieve more granularity and larger IRF horizons. Moreover, it could also be interesting to explore non-linearities in the model, since LPs allow for such specifications. As a robustness check, one could also perform a VAR analysis with the same specifications and see how different models generate different IRFs, stemming from the same data. Lastly, since the IMF also created another line of credit, the Precautionary and Liquidity Line (PLL), it would be insightful to see this analysis carried out on the countries that have access to it. Bearing in mind that this line of credit was designed to help states with economic conditions not as sound as those that got accepted into the FCL.

7. References

Abbritti, Mirko, Juan Equiza-Goñi, Fernando Perez de Gracia, and Tommaso Trani. 2020. "The Effect of Oil Price Shocks on Economic Activity: A Local Projections Approach." *Journal of Economics and Finance* 44 (4): 708–23.

Breitung, Jörg, and Ralf Brüggemann. 2023. "Projection Estimators for Structural Impulse Responses." *Oxford Bulletin of Economics and Statistics*, December.

Carcel, Hector, Luis A. Gil-Alana, and Peter Wanke. 2018. "Application of Local Projections in the Monetary Policy in Brazil." *Applied Economics Letters* 25 (13): 941–44.

Juan J. Dolado & Helmut Lütkepohl (1996) Making Wald tests work for cointegrated VAR systems, Econometric Reviews, 15:4, 369-386.

Dufour, Jean Marie, Denis Pelletier, and Éric Renault. 2006. "Short Run and Long Run Causality in Time Series: Inference." *Journal of Econometrics* 132 (2): 337–62.

Equiza-Goñi, Juan, and Fernando Perez de Gracia. 2019. "Impact of State-Dependent Oil Price on US Stock Returns Using Local Projections." *Applied Economics Letters* 26 (11): 919–26.

"Flexible Credit Line (FCL)." n.d. Accessed November 19, 2023. https://www.imf.org/en/About/Factsheets/Sheets/2023/Flexible-Credit-Line-FCL.

"IMF Conditionality." n.d. Accessed November 19, 2023. https://www.imf.org/en/About/Factsheets/Sheets/2023/IMF-Conditionality.

Inoue, Atsushi, and Lutz Kilian. 2002. "Bootstrapping Autoregressive Processes with Possible Unit Roots." *Econometrica* (70): 377–391.

International Monetary Fund. 2009. *Balance of Payments and International Investment Position Manual*. International Monetary Fund.

Jordà, Òscar. 2023. "Local Projections for Applied Economics." *Federal Reserve Bank of San Francisco, Working Paper Series* 2023 (16): 01–35.

Lusompa, Amaze. 2021. "Local Projections, Autocorrelation, and Efficiency." *The Federal Reserve Bank of Kansas City Research Working Papers*, March.

Montiel Olea, José Luis, and Mikkel Plagborg-Møller. 2019. "Simultaneous Confidence Bands: Theory, Implementation, and an Application to SVARs." *Journal of Applied Econometrics* 34 (1): 1–17.

Montiel Olea, J, and Plagborg-Møller, M . 2021. "Local Projection Inference Is Simpler and More Robust Than You Think." *Econometrica* 89 (4): 1789–1823.

Oscar Jordá, Paolo Angelini, Colin Cameron, John Cochrane, Tim-Othy Cogley, James Hamilton, et al. 2005. "Estimation and Inference of Impulse Responses by Local Projections." *American Economic Review* (95): 161–182.

Stata 18. 2023a. "Local Projection Impulse Response Functions."

Stata 18. 2023b. "Postestimation Tools for Lpirf."

Toda, Hiro Y, and Taku Yamamoto. 1995. "Statistical Inference in Vector Autoregressions with Possibly Integrated Processes." *Journal of Econometrics* (66): 225–250.

8. Appendix

8.1 Additional quarters

In the Appendix, we showcase the analysis for selected countries with larger forecast horizons. In the main body we have the same 10-quarter forecast horizon, since because of data availability some forecasts only amounted to 10 quarters ahead. Here, for the countries with a larger sample, we also show the IRFs for longer horizons. Namely, for Mexico we have a 20-quarter horizon, while for Poland we have a 40-quarter one.

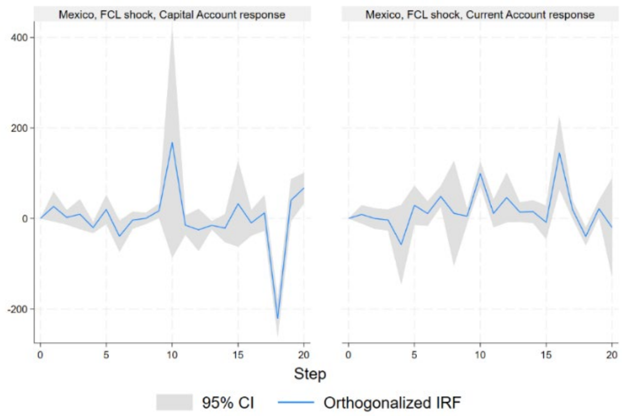

Figure 19, effect of a FCL shock on the Current and Capital Account in Mexico

Figure 20, effect of a FCL shock on the Financial Account in Mexico

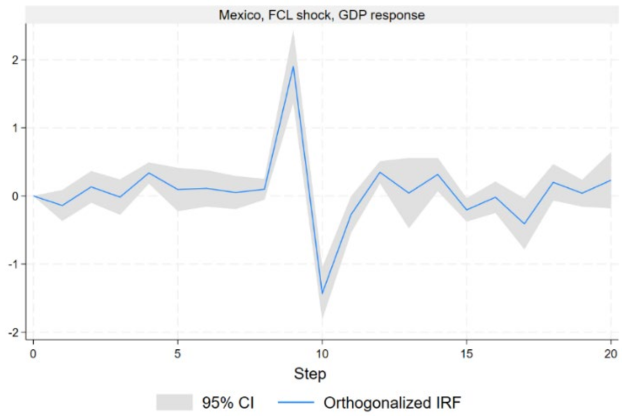

Figure 21 effect of a FCL shock on the GDP in Mexico

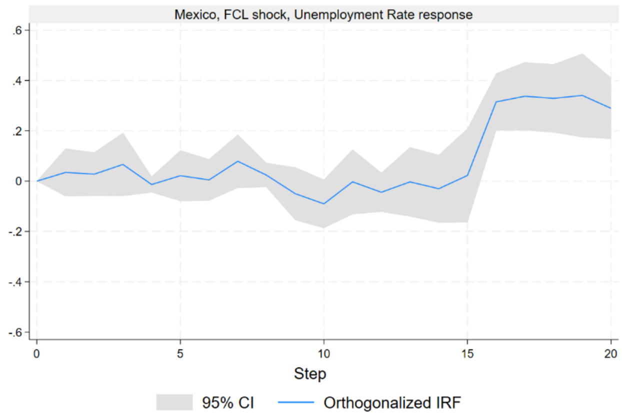

Figure 22 effect of a FCL shock on the Unemployment Rate in Mexico

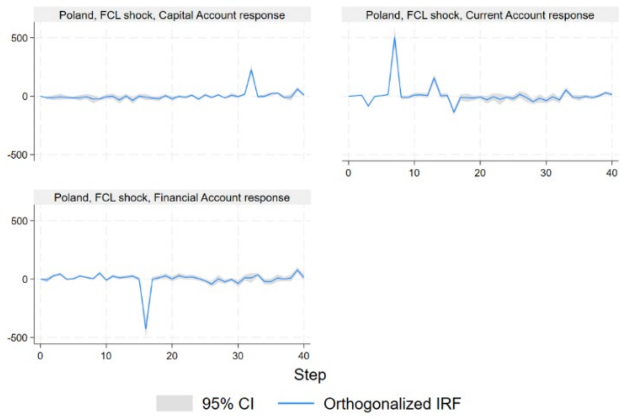

Figure 23 effect of a FCL shock on the Capital, Current and Financial Account in Poland

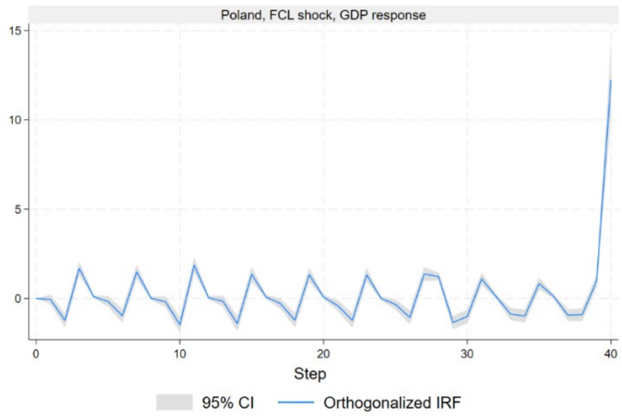

Figure 24, effect of a FCL shock on the GDP in Poland

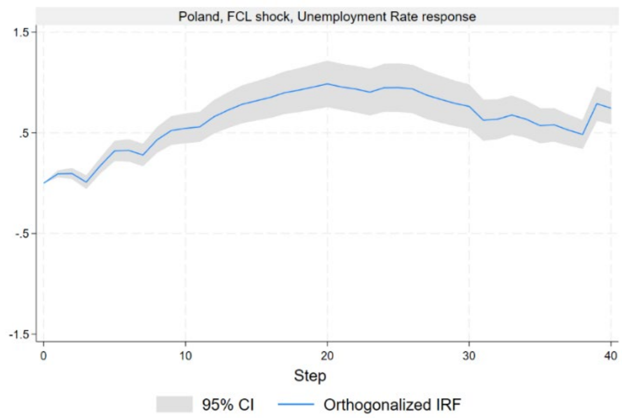

Figure 25, effect of a FCL shock on the Unemployment Rate in Poland

8.2 Other variables' responses

Moreover, as robustness checks, we also add here the remaining IRFs that were calculated in the analysis but not showed in the main body.

8.2.1 Chile

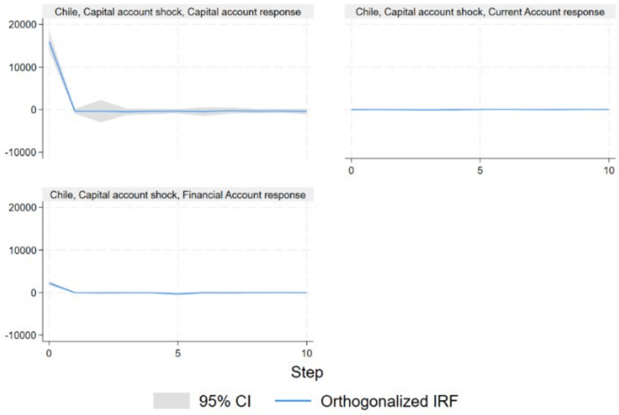

Figure 26, effect of a Capital Account shock on the Capital, Current and Financial Accounts in Chile

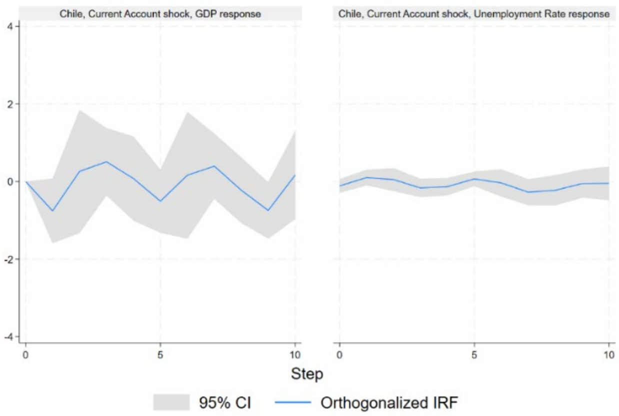

Figure 27, effect of a Current Account shock on the GDP and Unemployment Rate in Chile

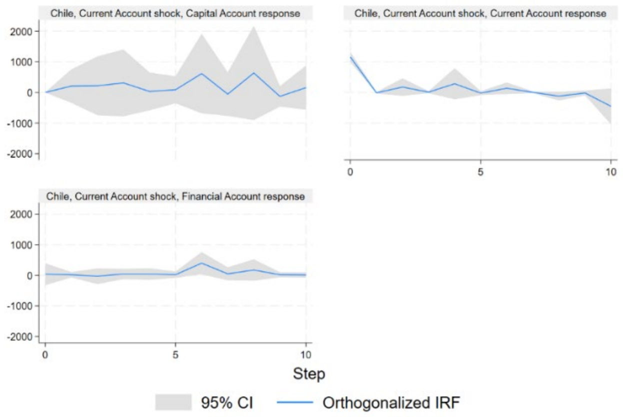

Figure 28, effect of a Current Account shock on the Capital, Current and Financial Accounts in Chile

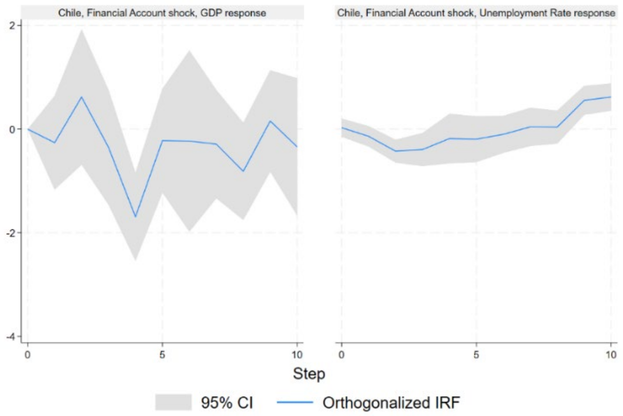

Figure 29, effect of a Financial Account shock on the GDP and Unemployment rate in Chile

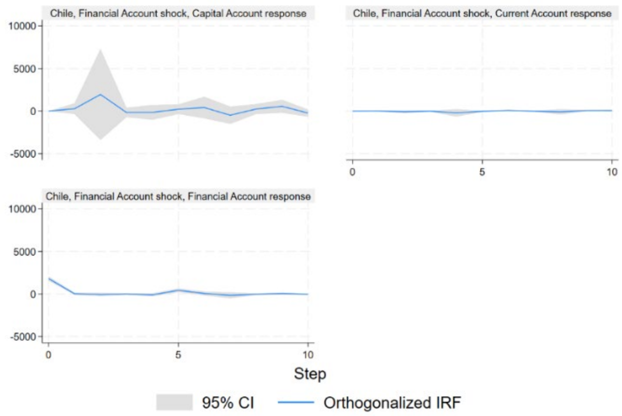

Figure 30, effect of a Financial Account shock on the Capital, Current and Financial Accounts in Chile

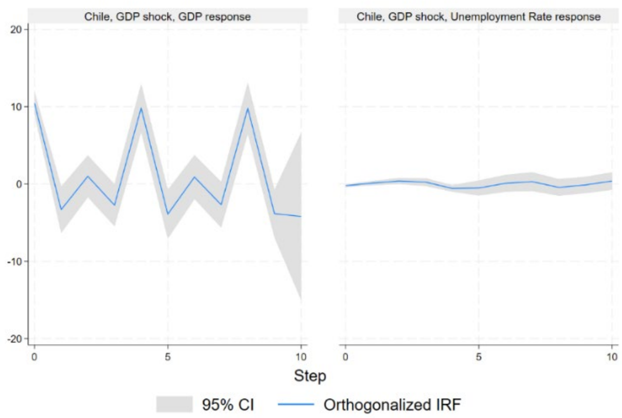

Figure 31, effect of GDP shock on the GDP and Unemployment Rate in Chile

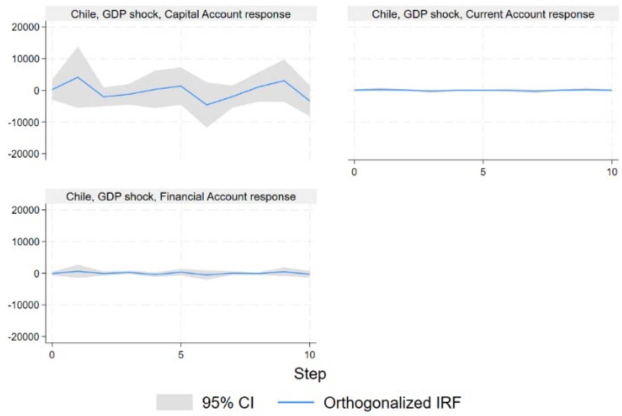

Figure 32, effect of a GDP shock on the Capital, Current and Financial Accounts in Chile

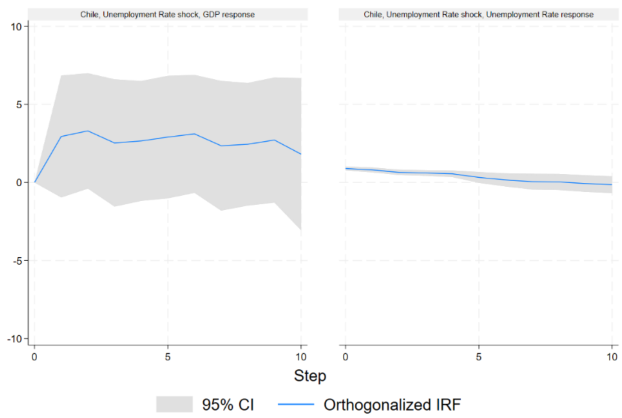

Figure 33, effect of an Unemployment Rate shock on the GDP and Unemployment Rate in Chile

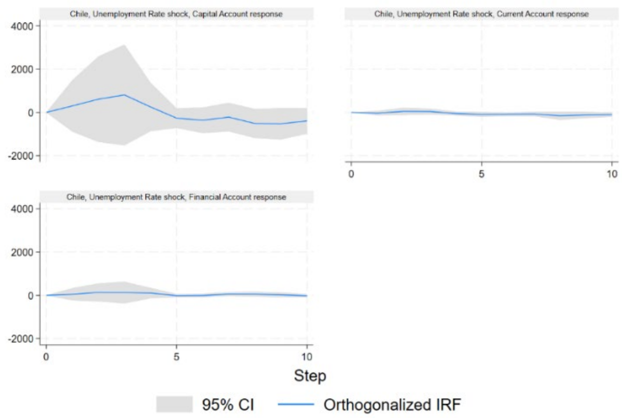

Figure 34, effect of an Unemployment Rate shock on the Capital, Current and Financial Accounts in Chile

8.2.2 Colombia

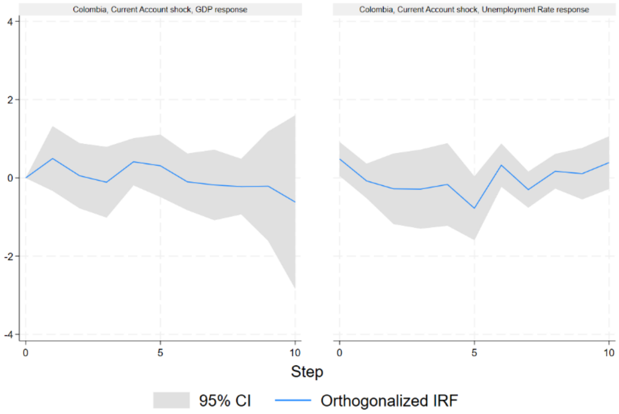

Figure 35, effect of a Current Account shock on the GDP and Unemployment Rate in Colombia

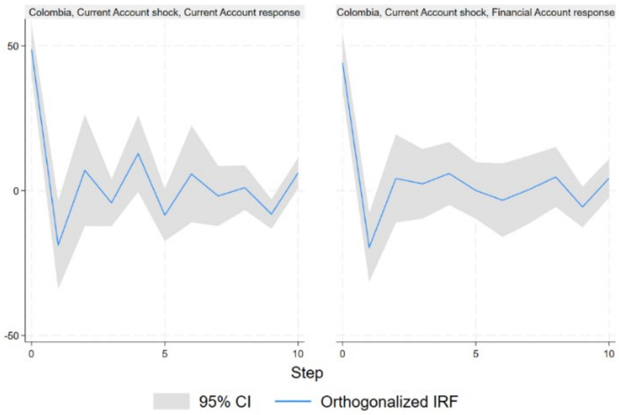

Figure 36, effect of a Current Account shock on the Current and Financial Accounts in Colombia

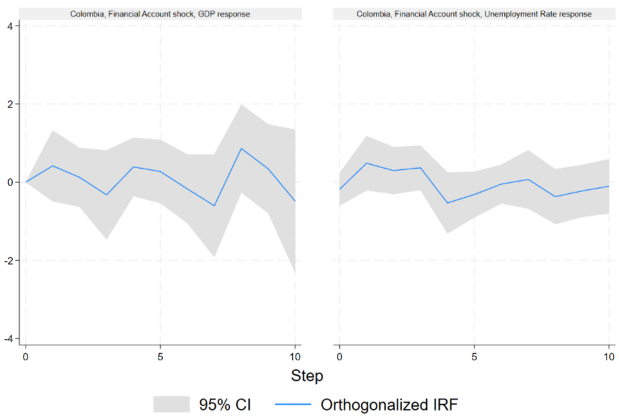

Figure 37, effect of a Financial Account shock on the GDP and Unemployment Rate in Colombia

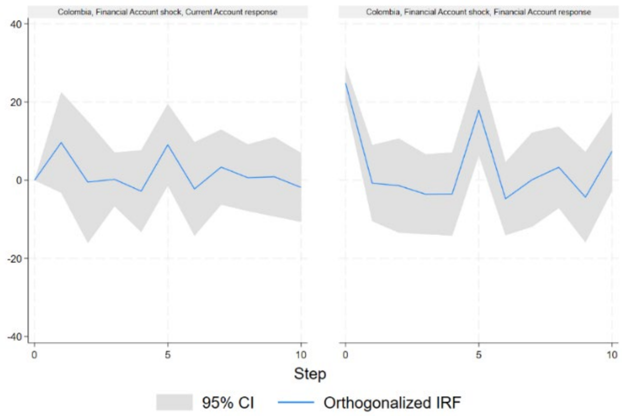

Figure 38, effect of a Financial Account shock on the Current and Financial Accounts in Colombia

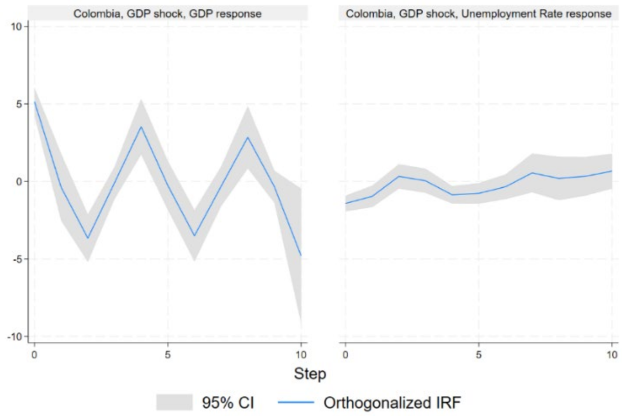

Figure 39, effect of a GDP shock on the GDP and Unemployment Rate in Colombia

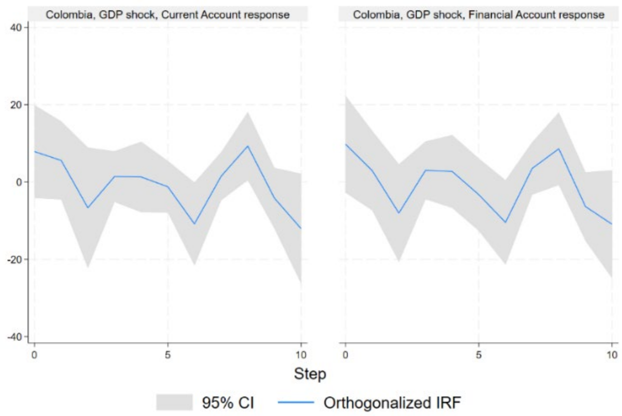

Figure 40, effect of a GDP shock on the Current and Financial Accounts in Colombia

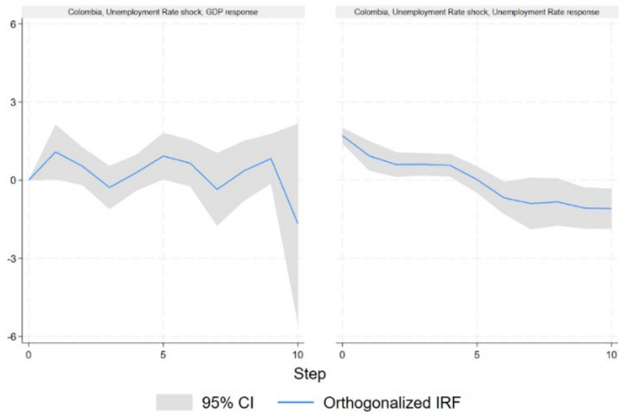

Figure 41, effect of an Unemployment Rate shock on the GDP and Unemployment Rate in Colombia

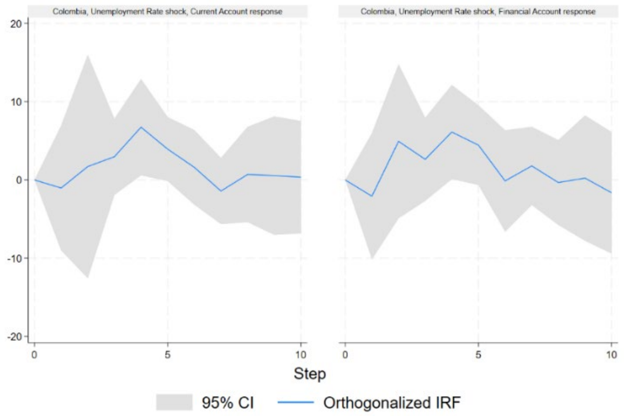

Figure 42, effect of an Unemployment Rate shock on the Current and Financial Accounts in Colombia

8.2.3 Mexico

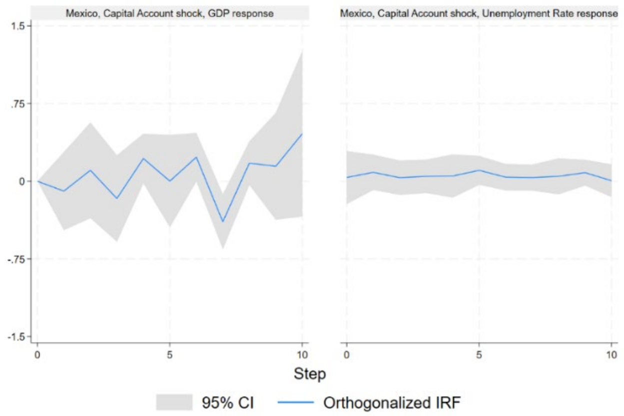

Figure 43, effect of a Capital Account shock on the GDP and Unemployment Rate in Mexico

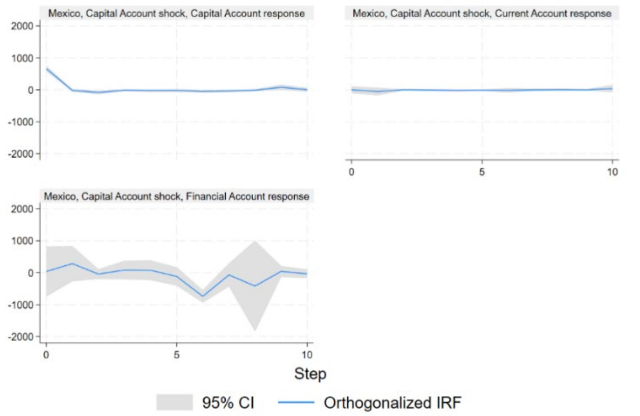

Figure 44, effect of a Capital Account shock on the Capital, Current and Financial Accounts in Mexico

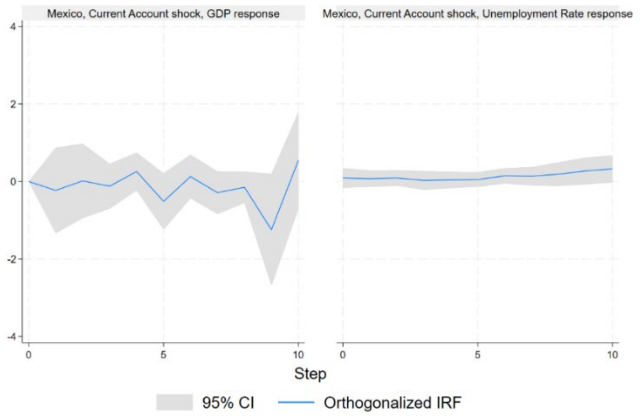

Figure 45, effect of a Current Account shock on the GDP and Unemployment Rate in Mexico

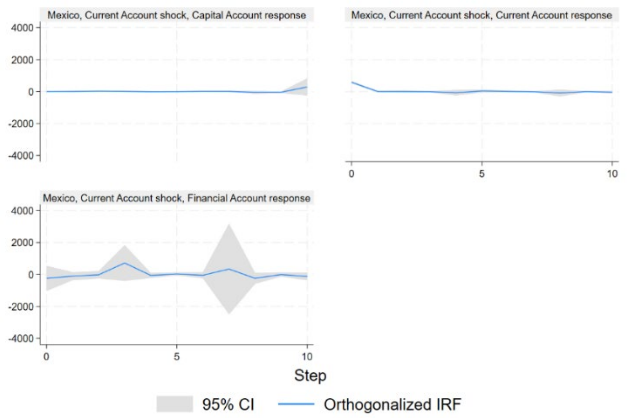

Figure 46, effect of a Current Account shock on the Capital, Current and Financial Accounts in Mexico

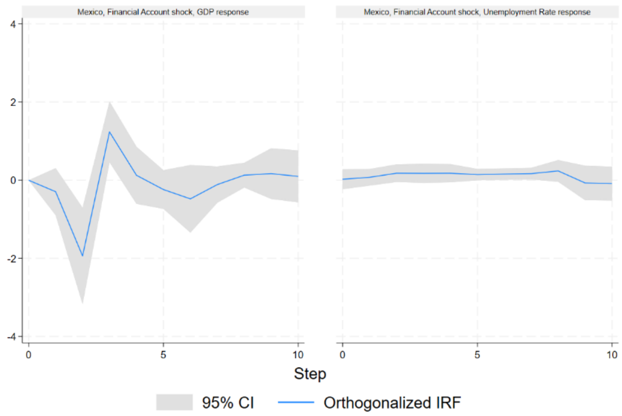

Figure 47, effect of a Financial Account shock on the GDP and Unemployment Rate in Mexico

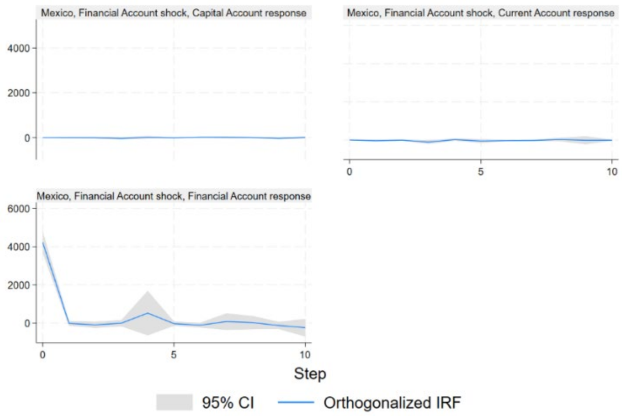

Figure 48, effect of a Financial Account shock on the Capital, Current and Financial Accounts in Mexico

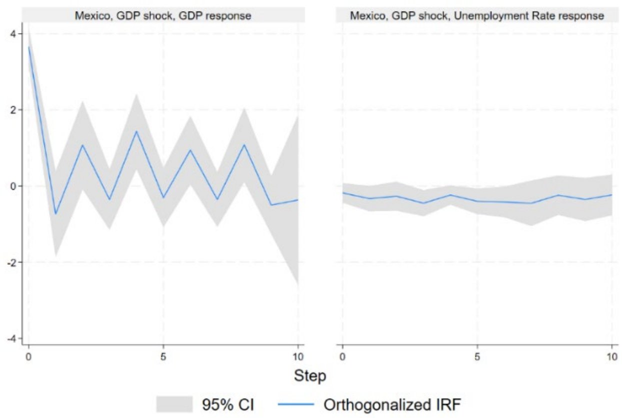

Figure 49, effect of a GDP shock on the GDP and Unemployment Rate in Mexico

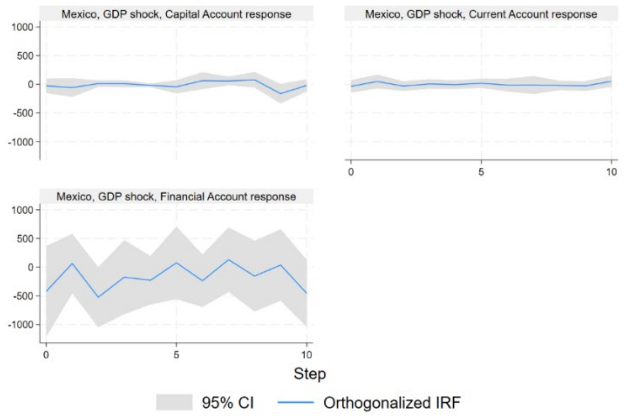

Figure 50, effect of a GDP shock on the Capital, Current and Financial Accounts in Mexico

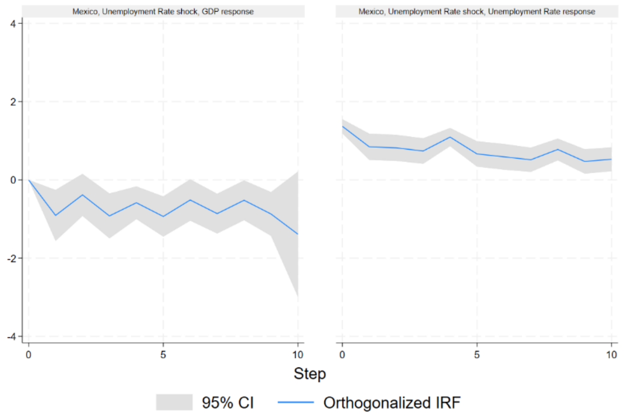

Figure 51, effect of an Unemployment Rate shock on the GDP and Unemployment Rate in Mexico

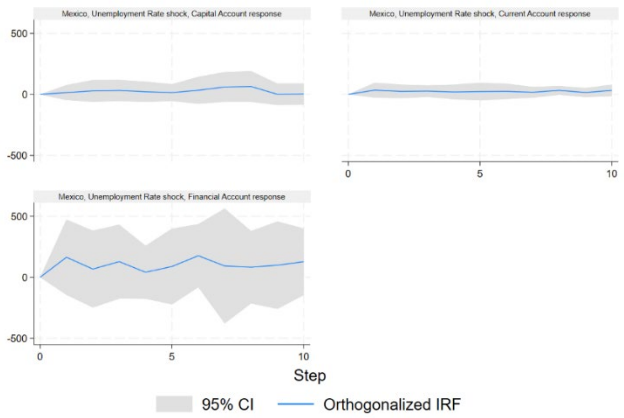

Figure 52, effect of an Unemployment Rate shock on the Capital, Current and Financial Accounts in Mexico

8.2.4 Peru

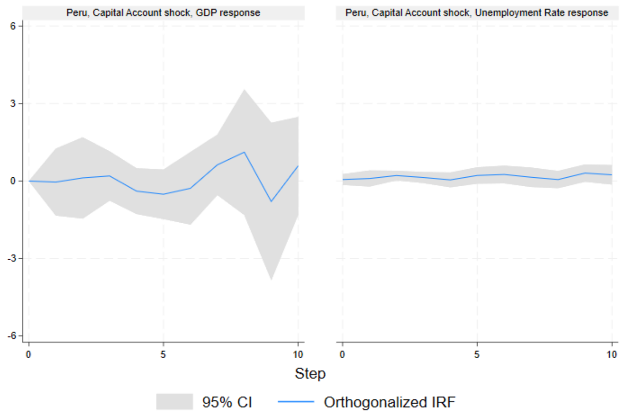

Figure 53, effect of a Capital Account shock on the GDP and Unemployment Rate in Peru

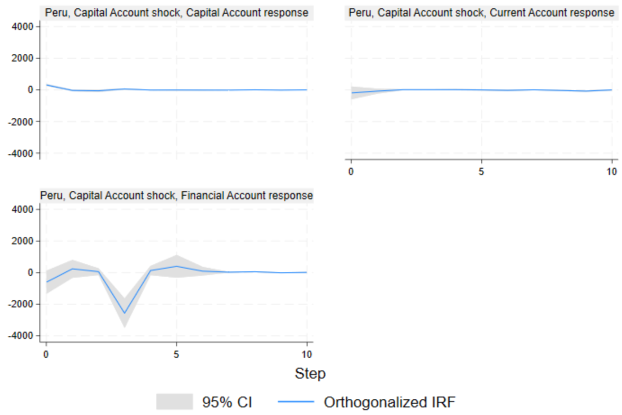

Figure 54, effect of a Capital Account shock on the Capital, Current and Financial Accounts in Peru

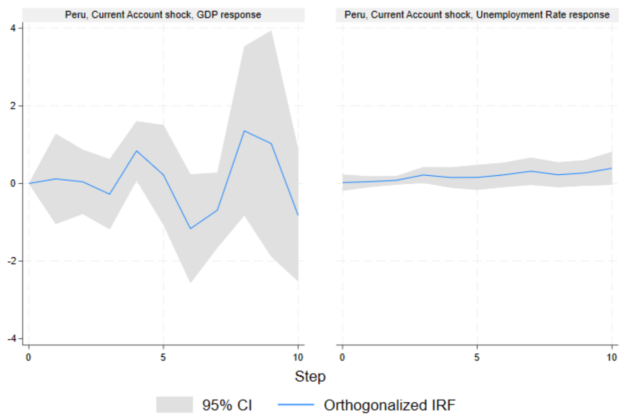

Figure 55, effect of a Current Account shock on the GDP and Unemployment Rate in Peru

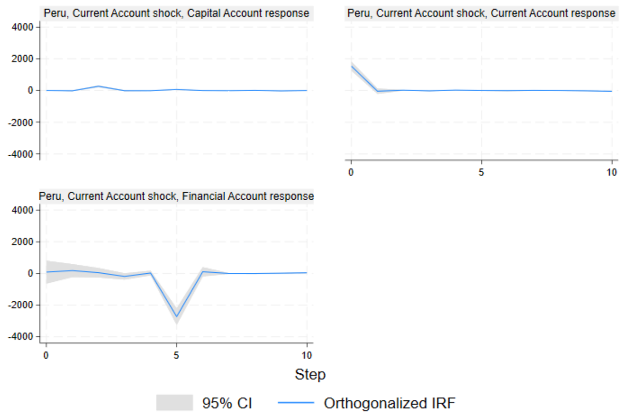

Figure 56, effect of a Current Account shock on the Capital, Current and Financial Accounts in Peru

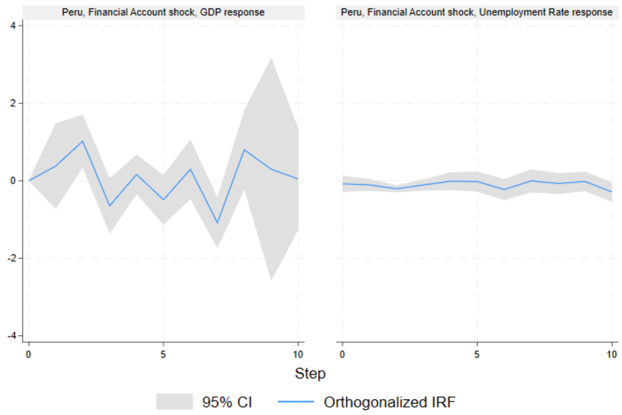

Figure 57, effect of a Financial Account shock on the GDP and Unemployment Rate in Peru

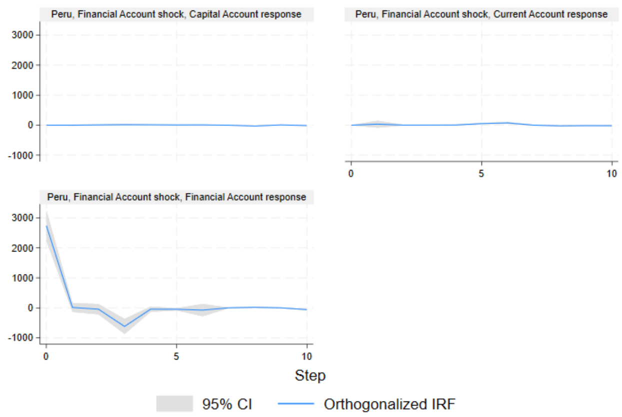

Figure 58, effect of a Financial Account shock on the Capital, Current and Financial Accounts in Peru

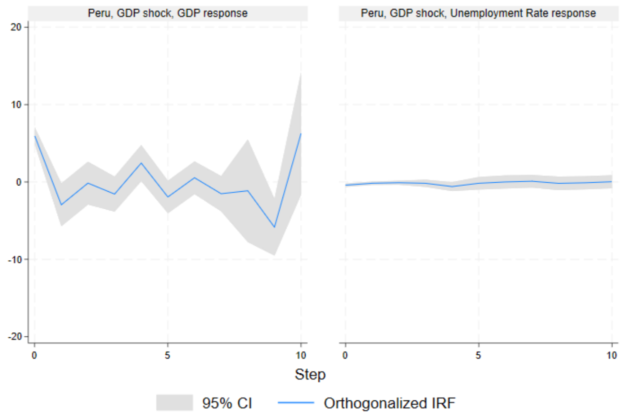

Figure 59, effect of a GDP shock on the GDP and Unemployment Rate in Peru

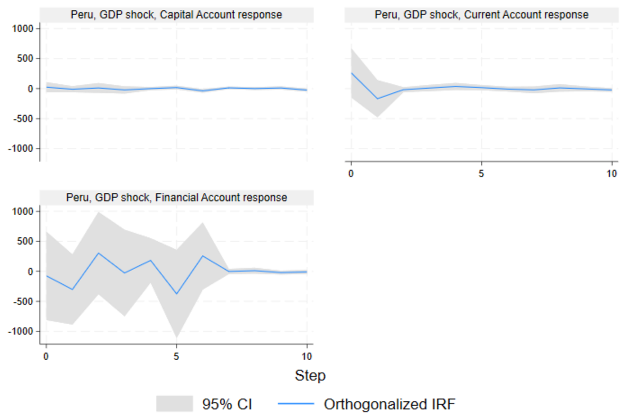

Figure 60, effect of a GDP shock on the Capital, Current and Financial Accounts in Peru

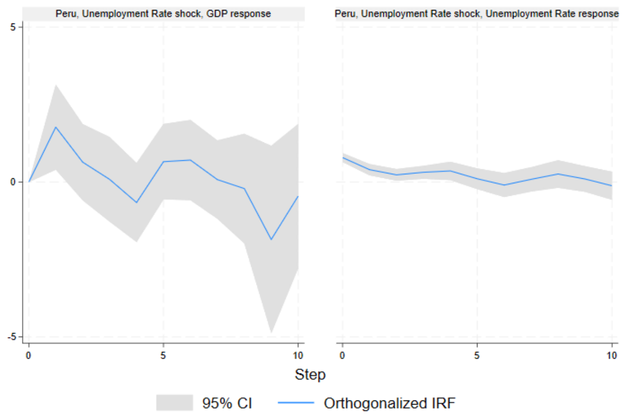

Figure 61, effect of an Unemployment Rate shock on the GDP and Unemployment Rate in Peru

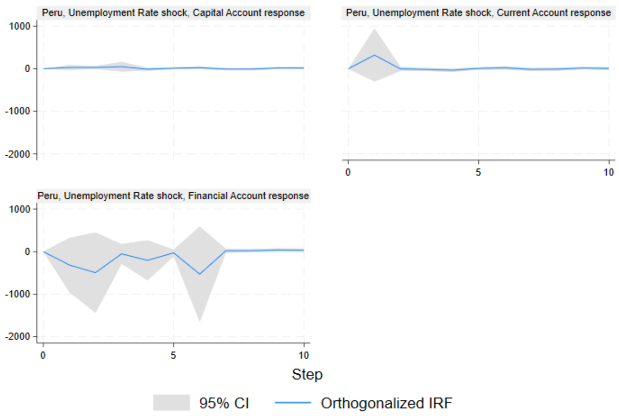

Figure 62, effect of an Unemployment Rate shock on the Capital, Current and Financial Accounts in Peru

8.2.5 Poland

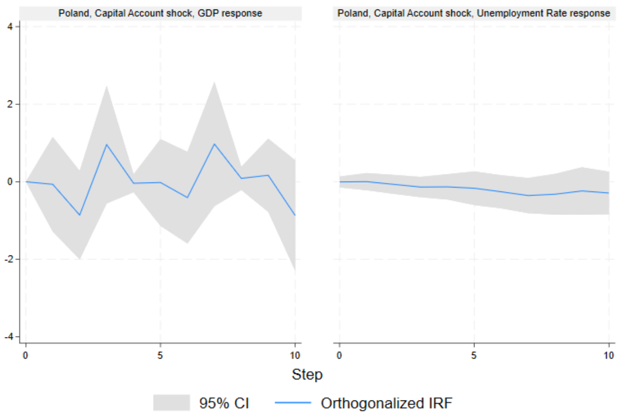

Figure 63, effect of a Capital Account shock on the GDP and Unemployment Rate in Poland

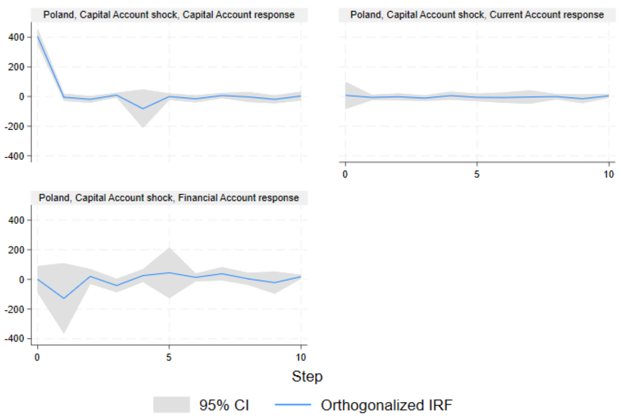

Figure 64, effect of a Capital Account shock on the Capital, Current and Financial Accounts in Poland

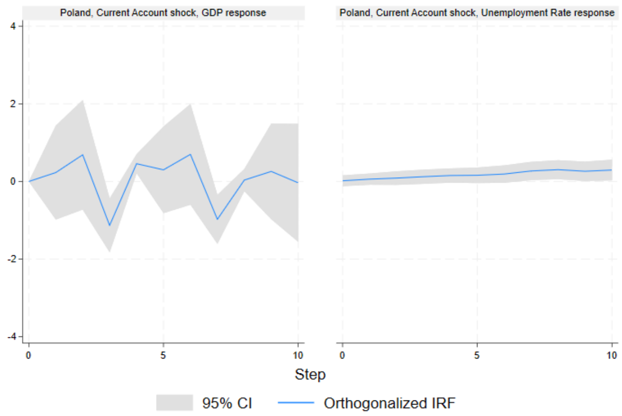

Figure 65, effect of a Current Account shock on the GDP and Unemployment Rate in Poland

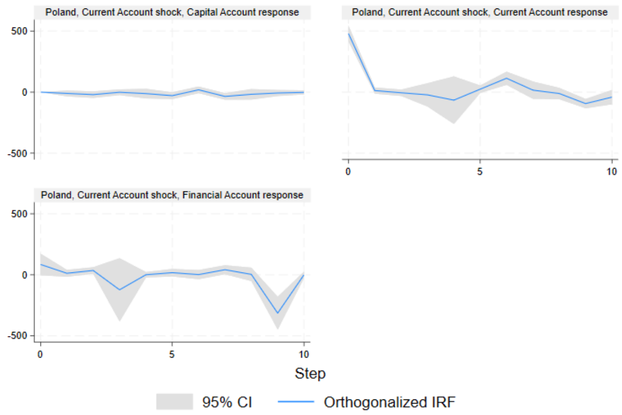

Figure 66, effect of a Current Account shock on the Capital, Current and Financial Accounts in Poland

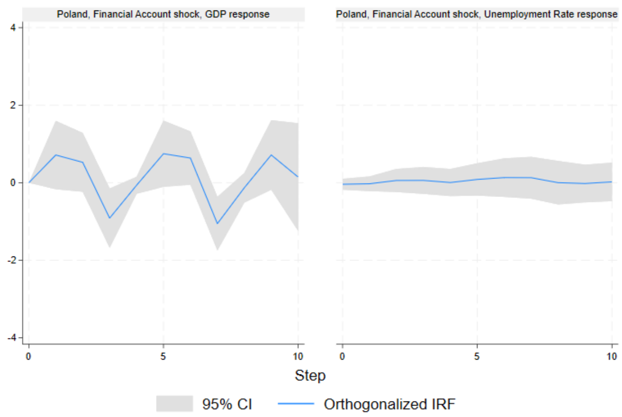

Figure 67, effect of a Financial Account shock on the GDP and Unemployment Rate in Poland

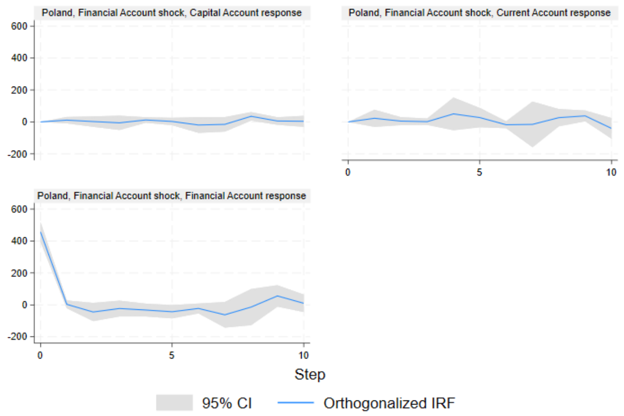

Figure 68, effect of a Financial Account shock on the Capital, Current and Financial Accounts in Poland

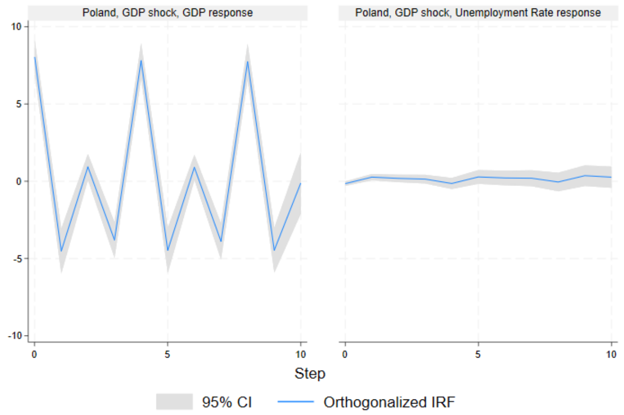

Figure 69, effect of a GDP shock on the GDP and Unemployment Rate in Poland

Figure 70, effect of a GDP shock on the Capital, Current and Financial Accounts in Poland

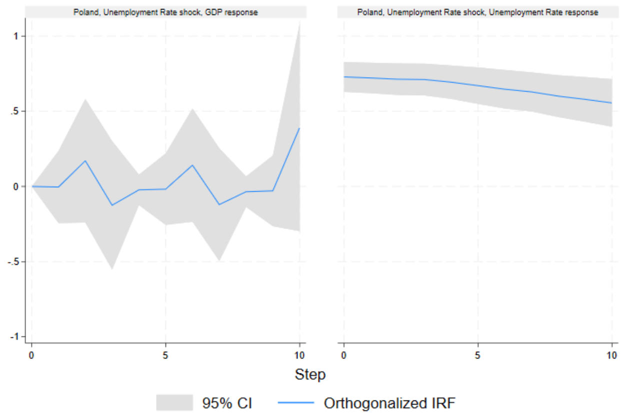

Figure 71, effect of an Unemployment Rate shock on the GDP and Unemployment Rate in Poland

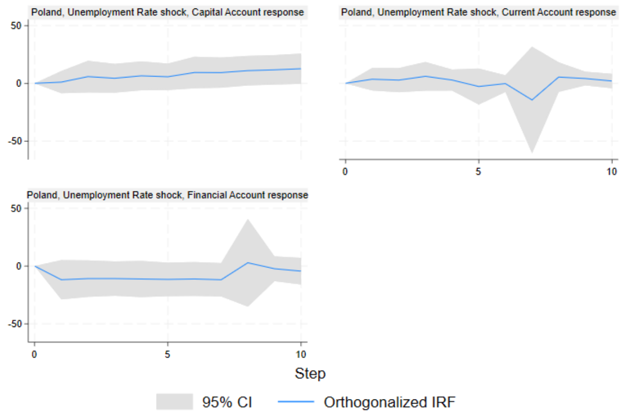

Figure 72, effect of an Unemployment Rate shock on the Capital, Current and Financial Accounts in Poland