# ENSO and its economic impact in the Peruvian economy: economic activity, inflation, and monetary policy design

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**Abstract**

Peru is a country that is vulnerable to weather disruptions caused by El Niño events. This paper evaluates the impacts of El Niño on inflation, aggregate output and sector-specific economic activity. We find consistent empirical evidence that El Niño shocks leave a footprint in the economy akin to a supply-side shock: it exerts inflationary pressures while simultaneously contracting GDP. The effects are more persistent on inflation than on aggregate economy activity. An exploration across sectors shows heterogeneous effects, and economic activity in primary sectors that are more immediate, larger but not persistent. On the contrary, non-primary sectors experience the negative effects that are smaller but far more persistent. We integrate the empirical results into a semi-structural model that incorporates four non-linear transmission channels through which El Niño affects the economy. This nonlinear framework presents a challenge for monetary policy design, as the economic uncertainty and the cost in stabilizing the economy depends on the frequency of El Niño events. A more hawkish monetary policy continues to influence de stabilization inflation dynamics in the presence of large scale shock, like El Niño. However, a precise calibration of monetary policy adjustments is needed to reduce negative effects on the trade-off between inflation and economic growth.

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# 1 Introduction

In recent years, the frequency, intensity, and unpredictability of adverse weather events have notably increased worldwide. It is estimated that in 2022, global GDP was reduced by 1.8%, primarily due to extreme weather events, and with disproportionate losses in low income regions (Rising, 2023). Global warming is anticipated to exacerbate this trend, leading to greater uncertainty about environmental conditions and future economic stability (Marticorena, 1999; Ribes et al., 2020). In response to this evolving reality, central banks have expanded their efforts to evaluate the wide-ranging impacts of climatic events on overall macroeconomic stability, as highlighted by Schnabel (2022).

One important physical risk for several economies, including Peru, is the El Niño event. El Niño-Southern Oscillation (ENSO) is an irregular but recurrent climate phenomenon that is responsible for the most dramatic year-to-year variation in global climate conditions (Greenberg, 2023). Cai and Santoso (2023) found that ENSO events are happening more frequently due to climate change and leading to more intense weather events, such as droughts, floods, and heatwaves. Throughout history, the El Niño-Southern Oscillation has significantly influenced weather patterns in Peru and had substantial economic impacts (Vargas, 2009). Major ENSO events in 1982-1983 and 1997-1998 caused economic losses equivalent to 11.6% and 6.2% of annual GDP, respectively (Senamhi, 2014). Future projections by Callahan and Mankin (2023) estimate even with current national commitments to reduce emissions, the increased frequency and intensity of ENSO events will cost the global economy $84 trillion this century.

This research delves into the case of Peru, a country vulnerable to the effects of the El Niño, to understand how ENSO shocks influence inflation, aggregate output, and sector-specific output. In particular, this paper aims to address the following questions: What is the dynamic response of inflation and economic activity after El Niño shock? What are the implications of these types of shocks for the design of monetary policy?

We explore the significance of anomalous weather shocks caused by ENSO on the Peruvian economy using three methodologies: Smooth Local Projections, a TVP-VAR and a Threshold-BVAR model.[1] This empirical exploration allows us to observe stylized facts about the effects of El Niño shocks on inflation and economic activity, and evaluate the uniformity of these shocks across sectors of the economy. We find consistent evidence that El Niño causes similar effects to the economy as a supply-side shock, by exerting inflationary pressures while simultaneously contracting GDP. The impacts across sector are heterogeneous. The reduction in economic activity in primary sectors is more immediate and substantial when compared to non-primary sectors, where the negative effects are smaller and take additional time to manifest, but far more persistent.

Finally, we assess the significance of El Niño for inflation and output stabilization by integrating our empirical findings with a semi-structural model that reflects these empirical observations, via impulse response matching. Our semi-structural model incorporates the asymmetry of the El Niño shock by including four nonlinear transmission channels, each consistent with our empirical results and dependent on the El Niño coastal index level (ICEN, for its acronym in Spanish).

[1] For the estimation of dynamic effect of the El Niño on aggregate macroeconomic variables we use a Local Projection estimator as in (Jordà, 2005). However, sector production indices are more noisy so to avoid the excessive variability of the LP estimator we use a Smooth Local Projections (see Barnichon and Brownlees, 2019 ). For the TVP-VAR-SV model we follow Canova and Pérez Forero, 2015 and for the Threshold-BVAR model we closely follow Alessandri and Mumtaz, 2019.

When the ICEN index exceeds a value of one, two channels are activated: (i) an inflationary channel, driven by rising food prices, which in turn triggers (ii) a demand channel, as higher food prices reduce consumers' disposable income which reduces demand. And when El Niño shock intensifies and the ICEN index surpasses a level of two, a couple of additional channels are activated: (iii) a potential GDP loss channel, due to extreme weather events like droughts and floods that disrupt production and damage infrastructure, and (iv) an inflation expectation channel, where persistent inflation and production disruptions lead to heightened inflation expectations.

This model enables us to explore the implications of climate-related shocks, alongside other structural disturbances, for monetary policy design. Our findings underscore the importance of accounting for the intensity of El Niño and the sensitivity of monetary policy in devising strategies to stabilize the economy. The nonlinear and multifaceted nature of the ICEN shock, as a particular type of supply shock in the economy, presents unique challenges, necessitating a careful balance between controlling inflation and ensuring economic stability.

In this nonlinear framework, economic uncertainty and the costs of stabilizing the economy are closely tied to the frequency of El Niño events. The irregular and unpredictable nature of these climate shocks complicates the formulation of effective monetary policies. However, a more hawkish monetary policy, characterized by higher interest rates and tighter monetary conditions, continues to play a crucial role in stabilizing inflation dynamics in the presence of large-scale shocks like El Niño.

However, the effectiveness of such policies must be carefully evaluated, considering the potential trade-offs between controlling inflation and supporting economic growth. Stabilizing inflation come at the cost of output gap stabilization. While inflation, core inflation, and inflation expectations exhibit a slightly smaller response compared to a less aggressive monetary stance, the differences are modest. In contrast, the output gap and foreign exchange depreciation show significantly more pronounced responses. These findings underscore the importance of carefully calibrating monetary policy to minimize the adverse impacts on both inflation and real economic activity.

The paper is structured as follows: Section 2 provides the literature review. Section 3 presents an empirical exploration of the economic consequences of El Niño on inflation and both aggregate and disaggregated GDP. In Section 4 we incorporate a transmission mechanism of ENSO in a semi-structural model, which we match with our empirical results. Through the lens of this model we are able to discuss monetary design after these shocks. Finally, the paper elaborate conclusions in Section 5.

## 2 Literature Review

This paper draws on empirical literature that examines the effects of anomalous temperature changes on the economy. Hsiang et al. (2017) observe that in the U.S., a 1°C increase in temperature, on average, results in a 1.2% contraction in GDP. Colacito et al. (2019) find a 1°F increase in summer temperatures in the U.S., reduced annual growth rates by between 0.15 and 0.25 percentage points. Using a time series, Kim et al. (2021) observe that even in a developed economy like the U.S., increases in severe weather can result in persistent reductions in growth and disrupt price stability.

Using annual data from 180 economies between 1950-2015, Acevedo et al. (2020) show that, in countries with relatively low average temperatures, rising temperatures have a marginally positive effect on output. However, the effect on countries with warmer climates is negative, and these negative effects appear stronger in developing economies (Bandt et al., 2021). Dell et al. (2012) find that elevated temperatures depress economic growth rates in developing economies, and negatively impact agricultural output, industrial production and political stability. Faccia et al. (2021) show that rising temperatures may increase inflation via higher food prices in the short run, and although these effects occur in both advanced and emerging economies, it is more pronounced in the latter group.

Chirinos (2021) finds that, if current global temperature deviations persist, income per capita in Peru could decrease by 9% by 2050 and by 22% by 2100 (compared to the income per capita that would be expected in 2050 and 2100, respectively, if the temperatures maintains a similar trend than between the years 1960 and 1990), with agriculture and fishing being the most affected sectors. He stresses the importance of developing better models to evaluate and respond to climate change. In her study on Peru, Vargas (2009) projected that a 2°C increase in temperature, coupled with a 20 percent rise in precipitation variability (deviation of rainfall from its sample average) by 2050, could result in a 20 percent reduction in the country's potential GDP.

Evaluating data of past ENSO in Peru, CEPAL (2014) concludes that El Niño and La Niña have caused significant economic damage, particularly affecting fishing, agriculture, and infrastructure. The report emphasizes the necessity of utilizing climate models to estimate ENSO's impacts, which will aid in planning adaptation and mitigation strategies. Cashin et al. (2016) observe that the impacts of El Niño on inflation and GDP vary greatly by country, and Peru experienced a greater decrease in GDP and more inflation than most of the countries studied.

Our research builds on previous studies that have documented the inflationary consequences of natural disasters. Faccia et al. (2021) developed a two-country, two-sector model to explore how climate shocks influence inflation. Their findings show that a temperature shock in the home country causes an immediate sharp increase in the prices of domestically produced food and, consequently, a spike in overall inflation due to the flexibility of food prices. However, this effect tends to dissipate quickly, or may even slightly reverse, over the medium term. Using annual panel data for 107 countries and VAR analysis, Mukherjee and Ouattara (2021) documented that temperature shocks result in inflationary pressures that can last years.

This paper is also adds to recent literature that studies the categorization of climate risks as supply or demand shocks. Ciccarelli and Marotta (2024) use data from a sample of OECD countries from 1990–2019 and a VAR model show that physical risks act like negative demand shocks while transition risks induce downward supply movements. On the other contrary, Pozo and Rojas (2024) observe that climate disasters data across a sample of developed and developing economies provide evidence that physical risks from climate-related events act as negative supply shocks: are inflationary and lead to contractions in both GDP growth and the output gap, and, importantly, these effects are compounded for low-income countries.

We aim to contribute to this empirical literature by documenting the impacts of extreme temperature anomalies resulting from ENSO in Peru, an emerging market economy that is exceptionally susceptible to weather shocks. We capitalize on El Niño's exogeneity to investigate how climate-related shocks impact both inflation and output. We further explore the differentiated effects of El Niño across sectors, documenting distinct patterns of shock propagation within these industries.

Additionally, we also contribute to the literature that studies the trade-off between output gap and inflation stabilization in the face of sector-specific shocks or relative prices shocks (Aoki, 2001; Blanchard and Gali, 2007; Auclert et al., 2023). Using a simple semi-structural model that integrates our empirical findings, we analyze the implications of El Niño on inflation, output gap dynamics, and monetary policy actions within a general equilibrium framework.

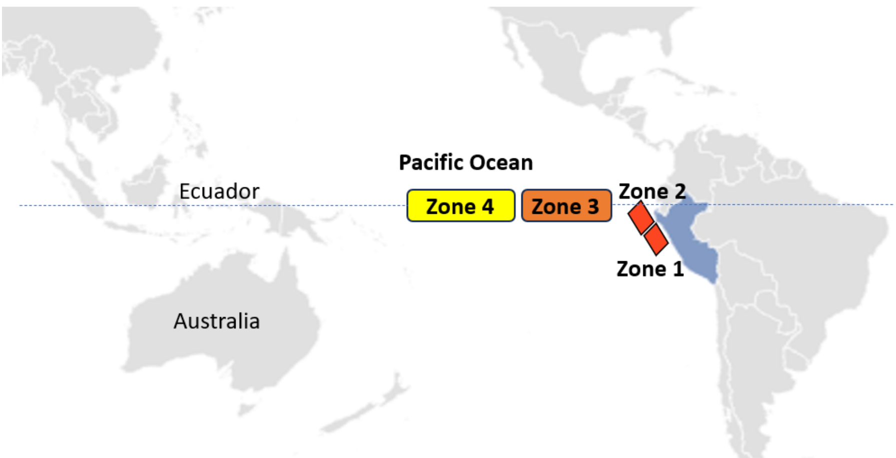
# 3 Empirical exploration

This section presents our empirical strategy to characterize the dynamic effects of El Niño on the Peruvian economy, by using impulse responses. First, an overview of the data involved in the analysis is provided, including the weather data used to identify El Niño shocks. Second, three methodologies are presented to estimate the impulse responses of macroeconomic and sectoral variables to these shocks: Smooth Local Projections, a TVP-VAR, and a Threshold-BVAR.

## 3.1 ENSO and Local Variation

El Niño-Southern Oscillation (ENSO) is a periodic, large-scale disruption to the climate system in the central and eastern tropical regions of the Pacific Ocean. Two main phases are identified: El Niño, characterized by the warming of sea surface temperatures, and La Niña, characterized by below-average sea surface temperatures. These phenomena occur cyclically, but La Niña events are typically shorter in duration and less frequent than El Niño events. El Niño occurs every two to seven years and have dramatic impacts on temperature, droughts, and rainfall. This paper will focus on a type of ENSO, El Niño Costero, which is an ENSO that strikes in the coastal regions of Peru and Ecuador. Figure 1 presents the El Niño Zones.

**Figure 1.** *El Niño Zones*

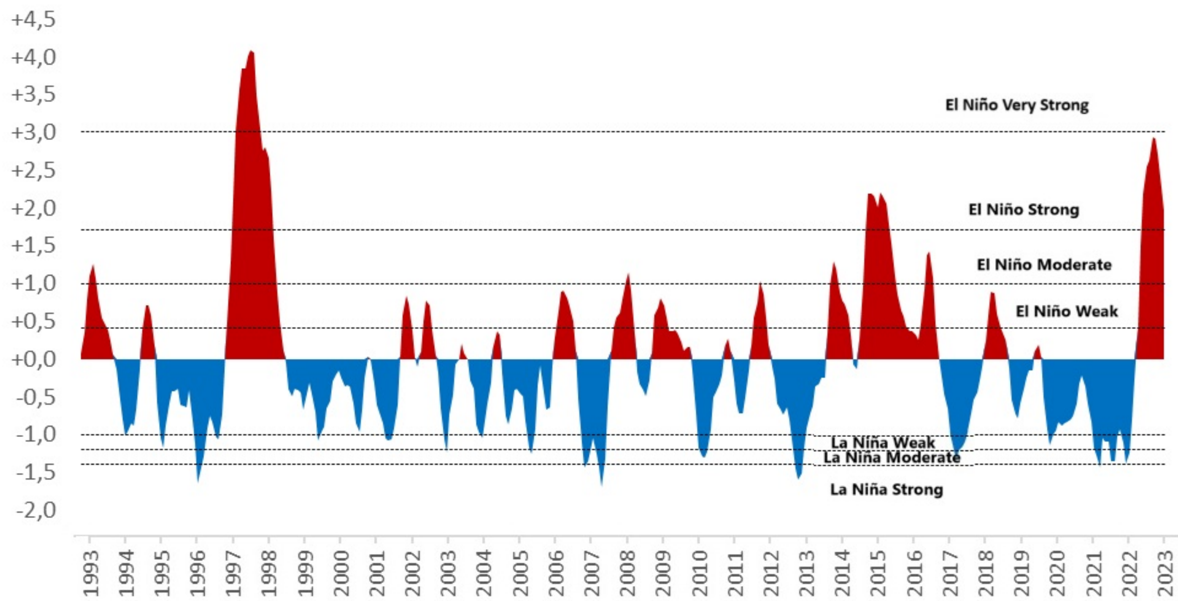



The Peruvian ENSO center, Estudio Nacional del Fenómeno del Niño (ENFEN), monitors sea surface temperatures to inform the ICEN index (Índice Costero El Niño), which determines the occurrence and magnitude of El Niño Costero. This index is derived from the Extended Reconstructed Sea Surface Temperature series (ERSST) reported monthly by NOAA (National Oceanic and Atmospheric Administration). The calculation involves taking the 3-month moving average of sea surface temperature anomalies, relative to the long-term mean (average between the years 1981-2010), for the 1+2 zone of the Pacific Ocean. Figure 2 plots the time series of this ICEN index and Table 1 presents the different categories for El Niño and La Niña according to its ICEN index value.

**Table 1.** *ICEN Categories*

| | Category | Threshold |
|---|---|---|
| El Niño | Very Strong | $ICEN > 3.0$ |
| | Strong | $3.0 \geq ICEN > 1.7$ |
| | Moderate | $1.7 \geq ICEN > 1.0$ |
| | Weak | $1.0 \geq ICEN > 0.4$ |
| Neutral | | $0.4 \geq ICEN > -1.0$ |
| La Niña | Weak | $-1.0 \geq ICEN > -1.2$ |
| | Moderate | $-1.2 \geq ICEN > -1.4$ |
| | Strong | $-1.4 \geq ICEN$ |

**Figure 2.** *ICEN Index and El Niño Costero*




Throughout history, the ENSO has significantly influenced weather patterns in Peru and had substantial economic impacts. Table 2 provides an overview of the significant El Niño events in Peru. Since 1980, there have been eleven El Niño events categorized as moderate or greater (1.0 or higher on the ICEN Index), with three reaching a peak intensity classified as 'strong' and two as 'very strong'. Major ENSO events in 1982-1983 and 1997-1998 caused economic losses equivalent to 11.6% and 6.2% of annual GDP, respectively (Senamhi, 2014). During both periods, severe flooding in the north and droughts in the south disrupted agriculture and damaged infrastructure. Even shorter, more moderate ENSO events in 1992 and 2014 led to GDP contractions of 2.5% and 2.3%, respectively (BCRP, 1992, 2014). The most recent El Niño in 2023-2024 was characterized by intense rains along the north coast and drought in the Andes, resulting in a 1.1% drop in GDP in 2023 (BCRP, 2023). Its effects are not only limited to economic damages. For example, the ENSO in 2017 displaced more than 300,000 individuals (Raissi et al., 2015).

**Table 2.** *An overview of significant El Niño Events: 1980-2024*

| Event | Dur. (months) | Peak severity | Event overview |
|---|---|---|---|
| 9/1982-9/1983 | 13 | Very Strong | During this ENSO event, northern Peru suffered severe flooding from heavy rains and there were droughts in the south.[a] It is estimated this El Niño reduced GDP by 11.6%, and by 1988 the losses from the event reached a magnitude of $4.1 trillion.[b] |
| 2/1987-11/1987 | 8 | Moderate | N.A. |
| 3/1992-6/1992 | 4 | Strong | GDP dropped by 2.5% in 1992 as a result of El Niño[c]. |
| 4/1993-6/1993 | 3 | Moderate | N.A |
| 4/1997-7/1998 | 16 | Very Strong | Northern Peru suffered severe flooding from heavy rains. Rainfall in urban areas was lower than in 1982-83, but catastrophic in the upper in Piura and Chira River Basin.[d] It is estimated this El Niño reduced GDP by 6.2%, and by 2003, the losses from the event reached a magnitude of $5.7 trillion.[e] |
| 7/2008-08/2008 | 2 | Moderate | N.A |
| 5/2012 | 1 | Moderate | N.A |
| 6/2014-7/2014 | 2 | Moderate | The 2.3% GDP contraction in 2014, the greatest annual reduction since 1992, can be attributed to El Niño and coffee leaf rust.[f] |
| 5/2015-3/2016 | 11 | Strong | N.A |
| 2/2017-4/2017 | 3 | Moderate | This El Niño contributed to a 0.8% drop in GDP in 2017.[g] |
| 3/2023-1/2024 | 11 | Strong | This El Niño resulted in intense rain on the north coast and drought in the Andes (September - December 2022), where frost persisted until January 2023. These weather conditions were unfavorable for both planting and harvesting seasons. This El Niño contributed to a 1.1% drop in GDP in 2023.[h] |

*Sources*: [a]Cross (2017), [b]Callahan and Mankin (2023), [c]BCRP (1992), [d]Cross (2017), [e]Callahan and Mankin (2023), [f]BCRP (2014), [g]BCRP (2023), [h]BCRP (2023)

### 3.2 Data

The empirical exploration relies on monthly economic databases from the Central Reserve Bank of Peru (BCRPData), from 1994M1-2023M12 regarding Peruvian economic variables of GDP indices, sector-specific production indices, and overall and food-specific inflation. In addition, from the FRED database we incorporate data on U.S. GDP and the Brent oil Index. Our data on El Niño is sourced from The Peruvian ENSO center, Estudio Nacional del Fenómeno del Niño (ENFEN). Following national convention, these events are categorized from "Weak" to "Very Strong", reflecting the magnitude to which sea surface temperatures (SST) deviate above historical averages for El Niño or below for La Niña, as shown in Table 1. We focus on Niño and Niña events with an intensity of Moderate or higher (ICEN higher than 1). Between 1993 and 2023, there are thirteen periods with qualifying anomalous events: eight El Niño and five La Niña events (See Figure 2).

### 3.3 Assessing the impact of the ENSO on GDP and Inflation: LP approach

Jordà (2005) Local Projections (LP) methodology is used to estimate the dynamic equilibrium response of inflation and GDP growth after an anomalous climate shock resulting from El Niño. In particular, following Ramey and Zubairy (2018), for an given outcome variable $y$, we estimate a non-linear specification of the form:

$$\begin{aligned} y_{t+h} &= (1 - I_t)[\alpha_{0,h} + \beta_{0,h} x_t + B_{0,h} X_t] + I_t[\alpha_{1,h} + \beta_{1,h} x_t + C_{1,h} X_t] + e_{t+h}\,, \\ I_t &= \mathcal{I}(x_t > 1)\,, \end{aligned} \tag{3.1}$$

where $h = 1, \ldots, 15$, and $x$ is the ICEN index, $\mathcal{I}(\cdot)$ is an indicator function, and as result $I$ is a dummy variable with value of 1 to indicate if an El Niño event (moderate or above) is identified based on the temperature index.

The coefficients of interest in equation (3.1) are $\beta_{1,h}$ for all $h$. These are dynamic multipliers that indicate the change at horizon $h$ of $y$ in response to an anomalous climate shock as a result of El Niño. The vector $X_t$ collects all the control variables considered. Common covariates for inflation and aggregate GDP growth as outcome variables include the following: lags of the dependent variable (six when the outcome is inflation and twelve in the case of GDP growth), six lags of the ICEN index, the oil price index growth, and US GDP growth. Additionally, when the outcome variable is GDP growth by specific sectors, a vector of contemporaneous controls is added, such as dummy variables, other sector indices, terms of trade, and liquidity of depository societies, which allow control for idiosyncratic dynamics.

The outcome variable $y_{t+h}$ is a measure of inflation or economic activity at moment $t+h$. $I$ is a dummy variable indicating if an El Niño event (moderate or above) is identified based on the ICEN index. Our identification relies on the exogeneity of the ICEN evolution, which is considered to be orthogonal to any economic development, at least in the short-term.

Although the ICEN index might evolve independently from the economy, it cannot be used to measure the impact of El Niño on the outcome variable due to its persistence. In fact, the ICEN index follows a persistent dynamics, and it is identified to be better captured by an ARMA(2,3) model, given by

$$x_t = \rho_0 + \sum_{j=1}^{2} \rho_j x_{t-j} + \varepsilon_t + \sum_{j=1}^{3} \phi_j \varepsilon_{t-j} \text{ with } \varepsilon_t \sim \mathcal{N}(0, \sigma_\varepsilon^2), \tag{3.2}$$

Table 3 presents the estimated coefficients from estimating this identified ARMA model applied to the ICEN index data. To use all information available, we estimated this model using the monthly sample from 1950m2 to 2024m4.

Since the ICEN index is serially correlated, it biases the coefficient on contemporaneous temperature away from its true value. Controlling for lagged values of ICEN is not sufficient to eliminate this bias. The only solution is to modify equation (3.1) by adjusting the lag structure of the dummy variable $I$, and including an ICEN shock, which is the Maximum Likelihood residual estimated in equation (3.2), denoted by $\hat{\varepsilon}_t$. See Appendix C for a complete discussion on the problem derived from the persistence of $x_t$ and for the lag structure of the dummy variable $I$. Therefore, we end up estimating the following specification:

$$y_{t+h} = (1 - I_{t-1})[\alpha_{0,h} + \beta_{0,h}\hat{\varepsilon}_t + B_{0,h}X_t] + I_{t-1}[\alpha_{1,h} + \beta_{1,h}\hat{\varepsilon}_t + C_{1,h}X_t] + e_{t+h} \quad (3.3)$$

**Table 3.** *ICEN as an ARMA(2,3) process*

| | Coef. | Std. Err. | $z$ | $P > \|z\|$ | [95% Conf. interval ] | |
|---|---|---|---|---|---|---|
| $\rho_0$ | -0.233 | 0.109 | -2.130 | 0.033 | -0.446 | -0.019 |
| $\rho_1$ | 1.712 | 0.077 | 22.37 | 0.000 | 1.562 | 1.862 |
| $\rho_2$ | -0.755 | 0.068 | -11.100 | 0.000 | -0.888 | -0.621 |
| $\phi_1$ | 0.301 | 0.091 | 3.310 | 0.001 | 0.123 | 0.479 |
| $\phi_2$ | 0.270 | 0.090 | 2.990 | 0.003 | 0.093 | 0.447 |
| $\phi_3$ | -0.659 | 0.089 | -7.380 | 0.000 | -0.833 | -0.484 |
| $\sigma^2_\varepsilon$ | 0.151 | 0.003 | 49.430 | 0.000 | 0.145 | 0.157 |
| Sample: | | | Feb-1950 to Apr-2024 (891 observations) | | | |

The LP model in equation (3.3) is estimated using the methodology developed by Barnichon and Brownlees (2019), which uses a B-spline smoothing method called smooth local projections (SLP). Impulse responses computed using SLP improve accuracy and interpretation while maintaining flexibility.

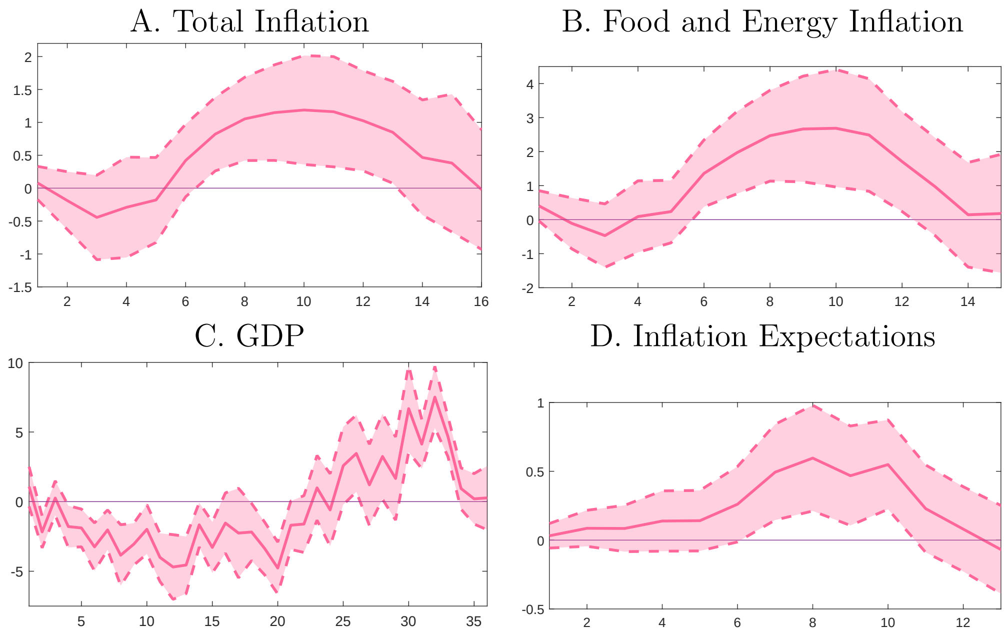
### Results

Figure 3 shows the LP impulse responses of macroeconomic variables to a ICEN shock, calibrated to simulate El Niño event that matches the historical average occurrence of this phenomenon in terms of duration and magnitude.[2] Each panel depicts the impact of an increase in temperature during El Niño events, represented by a rise in the ICEN Index from an initial value of 1, on a macroeconomic variables over time. The y-axis represents the percentage change of the macroeconomic variables, and the x-axis represents months after the shock. The red solid lines represent the mean response, while the red dashed lines represent the 68% confidence intervals.

Panel A in Figure 3 shows that after an El Niño shock hits the economy, inflation starts to rise after seven months to around 82bps and increases steadily until the peak effect of 119 bps is reached ten months later. Although it takes seven months for these inflationary effects to manifest to a statistically significant level, they are persistent. The inflationary effects begin to ease only after twelve months and resolve by the sixteenth month. Panel B provides evidence that the majority of the variation in the inflation response can be attributed to El Niño's high impact on food and energy inflation. The total inflation response mirrors that of food and energy inflation, showing a notable

[2] In particular, El ICEN shock is consistent with an El Niño event that has a duration of 9 months and a mean magnitude of 1.7. This is a Strong El Niño event category.

**Figure 3.** *LP: Effects of El Niño on aggregate macroeconomic variables*




*Note*: LP impulses to a one-degree change in the temperature during an El Niño event, i.e., an increase of one unit in the ICEN index (provided the initial ICEN index value is greater than 1). y-axis: Percentage change of the macroeconomic variable. x-axis: Months after the shock, where the black lines represent the mean response and the red lines represent the 86% confidence intervals.

reaction approximately six months after the shock, with an increase of around 136 basis points. Ten months later, this response is 2.69 percent higher. The response of Total inflation corresponds with that of food and energy inflation, which reacts significantly after six months to the shock by around 136bps, and ten months later it is 2.69 percent higher.

Panel C illustrates the GDP growth response to an ENSO shock. GDP experiences a significant decline, reaching a trough of about -4.77 percent. This negative impact intensifies over a three-month period before gradually diminishing. By the fifth month post-shock, the effects on GDP growth are still negative but less severe, around -1.69 percent.

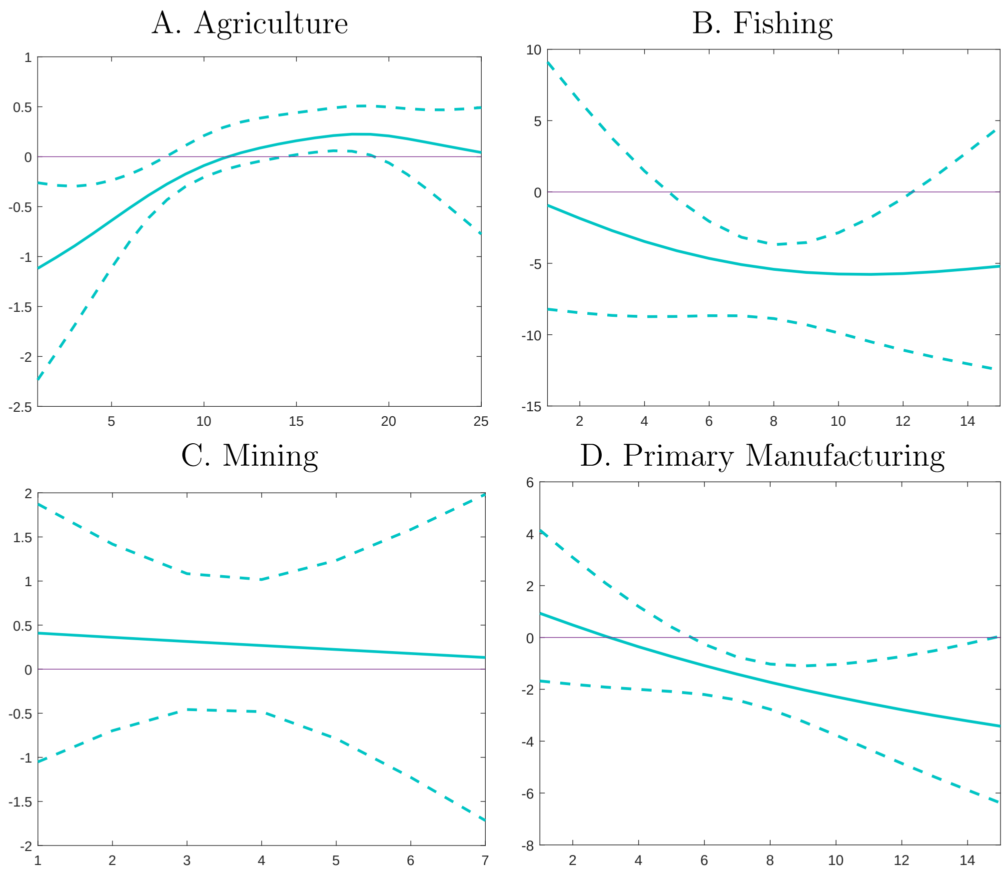
The overall level of GDP shows a more persistent decline. This enduring negative impact is due to the lack of a subsequent increase in growth rates that would offset the initial sharp decreases. The persistent decline in the level of GDP suggests that the shock has a lasting effect on the economy's productive capacity. This can be attributed to the destruction of capital caused by natural disasters such as landslides and mudslides. These events can lead to significant damage to infrastructure, buildings, and machinery, which are essential for production.

Finally, panel D illustrates the impact of an ENSO shock on inflation expectations. The initial response is positive, with a modest increase of 3.2 basis points. This upward trend continues, reaching a peak of approximately 60 basis points after eight months. Subsequently, the response begins to decline but remains above the initial level for an additional four months. The effects of the ENSO shock dissipate around the 14th month.

To gain more insight into the differentiated effects of El Niño, we computed the impulse responses across economic sectors, as reported in Figure 4 and Figure 5, for both primary and non-primary GDP sectors. Panels A, B and D in Figure 4 reveal the primary sectors most impacted by El Niño shocks: fishing, agriculture, and primary manufacturing. These sectors respond immediately to the shock, with fishing experiencing the most significant reduction in output, a decline of approximately 5.78%. Primary manufacturing decreases by 3.42%., while agricultural output drops by 1.11%. The impact on agriculture is similar to that on aggregate GDP, the response starts with a significant negative value of -1.1187, indicating a sharp initial decline in agricultural GDP growth. This trend continues, with values gradually becoming less negative but still indicating a decline. This suggests that the sector is experiencing a prolonged period of contraction.Around the 12th period, the response turns positive, peaking at 0.2252 in the 18th period. This indicates a temporary recovery or growth phase in agricultural GDP. However, while there is some recovery, the overall level of agricultural GDP remains below its initial level, indicating a permanent fall in the sector's GDP. The observed decline in agricultural GDP growth could be attributed to the destruction of farmland caused by heavy rains and flooding.

On the other hand, the effects on fishing and primary manufacturing and qualitatively quite similar and both dissipate around the 14th month. In contrast, mining (Panel C) shows negligible effects of an ENSO shock on mining sector GDP. Figure 5 illustrates the

**Figure 4.** *SLP: Effects of El Niño on Primary GDP sectors*

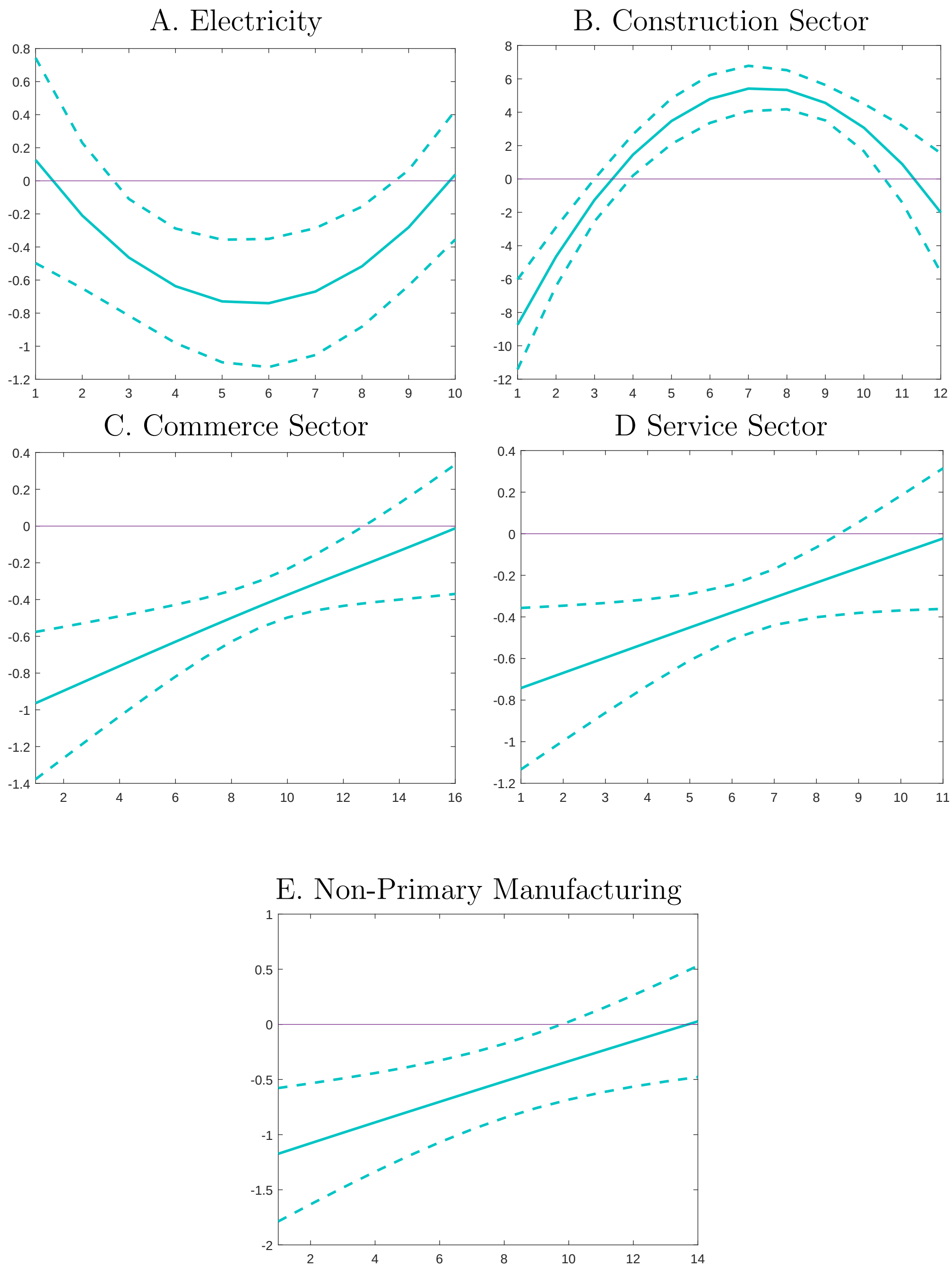



*Note*: SLP impulses to a one-degree change in the temperature during El Niño events (i.e An increase of one unit in the ICEN Index, provided the initial ICEN index value is greater than 1). y-axis: in percentage. x-axis: months after the shock. The black lines represent the mean response, while the red lines represent the 68% confidence intervals.

impulse responses of the non-primary sectors to an El Niño shock. Unlike the primary sectors, the non-primary sectors exhibit a less pronounced immediate response. The impacts on these sectors are in general more enduring, persisting longer than the effects observed in the primary sectors.

The impulse response of the construction sector's GDP to the ENSO shock is noteworthy. Initially, there is a significant decline of around -8.74%, indicating a sharp drop in GDP growth due to the ENSO shock. However, by the 4th period, the response turns positive, peaking at 5.42% in the 7th period. This suggests a strong recovery phase, likely driven by reconstruction activities following the ENSO shock. Nevertheless, this positive growth is not sustained, and the sector eventually stabilizes.

**Figure 5.** *Effect of an Increase of One Unit in the ICEN Index*




*Note*: SLP impulses to a one-degree to one degree change in the temperature during El Niño events (i.e a one-unit increment in the ICEN Index, conditional that the ICEN is above 1). y-axis: in percentage. x-axis: months after the shock. The solid lines represent the mean response, while the dotted lines represent the 68% confidence intervals.

In summary, the impulse responses of GDP across all economic sectors indicate a temporary decline in the growth rate (and a permanent decline in the GDP level) of these sectors. Only the construction and agriculture sectors show some stage of recovery. The primary sectors, which are more closely linked to potential GDP, experience a more significant decline. This suggests that it is pertinent to consider an impact on potential GDP, as we have already deduced from the impulse responses of aggregate GDP.

### 3.4 Robustness

Our previous analysis of the effects of El Niño on the Peruvian economy, using SLP impulse responses, captures the average impacts by aggregating all El Niño events. However, the intensity of specific El Niño events varies, which leads to a range of economic impacts. To gain insight into this temporal heterogeneity, we employ a Time-Varying Parameters Vector Autoregression with Stochastic Volatility (TVP-VAR-SV) approach to identify the effects of ICEN index shocks. Appendix A.1 describes the specification of the model.

We also explore the robustness of our SLP results by estimating the effects of the ICEN shocks using a Threshold BVAR approach. We consider that a value of the ICEN of 1 could trigger a regime switch. Appendix A.2 offers a complete description of of the model.

These results are consistent with our estimates using SLP impulse responses in Section 3.3, in terms of direction, size, and persistence.

#### Results

The robustness results are consistent with our estimates using LP impulse responses in Section 3.3, in terms of direction, size, and persistence. Panel A and B of Figure 8 in Appendix A show how the impulse responses of inflation and economic activity evolved over time following a shock in the ICEN Index. In general, we observe that positive temperature shocks cause an increase in inflation and contraction in GDP over time. The most pronounced responses correlate with severe El Niño episodes, specifically those in 1998, 2017, and most recently, 2022-2023.

Figure 9 in Appendix A illustrates the impulse responses within the Threshold BVAR model. We find that there are potential differences in the responses to shocks in the ICEN variable, depending on whether the initial conditions are below or above the threshold. The complete description of both models are presented in Appendix A.

### 3.5 Discussion

All our results from the previous empirical exploration provide evidence that El Niño shocks have similar effects on the economy as supply-side shocks, by exerting inflationary pressures while simultaneously contracting GDP. The impact on inflation is more persistent than that for aggregate output. This distinct economic pattern has important implications for monetary policy strategy, as El Niño shocks disrupt the conventional relationship between inflation and economic activity, akin to supply shocks. The central bank's response to these shocks would be limited or non-existent, to the extent that these shocks are temporary and do not influence inflation expectations. If the latter occurs, the risk scenario would become more complex, given the central bank's constitutional mandate to preserve monetary stability. We explore more about the complexities in the next section, through the lens of a semi-structural model.

Our results also show that even though the effects on aggregate economic activity are temporary, they are heterogeneous across sectors. The impact on primary sectors is more immediate and larger, but the effects on non-primary sectors while smaller, are far more persistent. Although the differentiation of the effects are important in themselves, in the following section we further discuss the aggregate consequences of El Niño on the Peruvian economy using a semi-structural model.

## 4 A semi-structural model with ENSO shocks

In this section, our goal is to evaluate how climate distress, in conjunction with other structural shocks, may be operating in the Peruvian economy and explore the implications for monetary policy design.

### 4.1 The model

We leverage our empirical results to calibrate a semi-structural model. In particular, we incorporate into the semi-structural model of Aguirre et al. (2022) four non-linear transmission channels through which El Niño affects the economy. These channels are consistent with our previous empirical results and depend on the level of the ICEN Index: As illustrated in the impulse response function of GDP in Figure 3, the ENSO shock results in a permanent reduction in the GDP level. Although GDP growth turns negative and later recovers, the increase is insufficient to offset the persistent initial decline in the GDP level. To capture this identified impact of El Niño on GDP, we assume that the ENSO shock have effects on potencial and output gap. El Niño causes a temporary reduction in potential interannual GDP growth, driven by the destruction of capital goods and loss of lives. The impact on the output gap is secondary, and we calibrate it as a fraction of the impact on potential GDP. Inflation expectations are also affected, but only in the case of a severe El Niño event. The (de-)anchoring of inflation expectations during an El Niño episode aligns with the observed increase in both the persistence and level of inflation expectations following extreme supply shocks, as noted in Velarde (2017). Finally, we characterize El Niño as an extreme supply shock, which results in an increase in both the level and persistence of food and energy inflation.

Altogether, when the ICEN index exceeds a value of 1, it triggers: i) an inflationary channel, due to a rise in food and energy prices, which causes ii) a demand channel, given that higher food prices can reduce consumers' disposable income and lead to a decrease in spending on other goods and services. As the El Niño shock becomes stronger and the ICEN index exceeds a value of 1.7, two more channels activate: iii) a potential GDP loss channel, as El Niño produces extreme weather conditions, such as droughts and floods, that disrupt production and cause infrastructure damage; and iv) the inflation expectation channel, as a large and persistent rise in inflation and the disruption in production induce households to expect more inflation.

In the following, we focus on presenting how El Niño events actives the four non-linear mechanisms within the semi-structural model, and defer a complete description of the model to the appendix B.1.

*The ENSO shocks and when they operate*

We consider that ENSO shocks are governed by an exogenous stochastic process, which is also persistent, and given by our estimated equation (3.2).

**Table 4.** *Nonlinear effects of ENSO*

| | Effect on ... | |
|---|---|---|
| $ICEN > 1$ | Inflation of food and energy | Output gap |
| $ICEN > 1.7$ | Inflation expectations | Potential GDP |

Consistent with our empirical estimation, we assume that the relationship between the extreme supply shock, El Niño, and macroeconomic variables is nonlinear and dynamic. We characterize this by making the effects of El Niño on output and inflation components dependent on the level of the ICEN index and whether it reaches certain thresholds. The nonlinear, asymmetric effect of ENSO shocks considered here is represented in Table 4. ENSO only have an impact on output gap and inflation of food and energy when it is bigger or equal than than 1. the model considers another non-linearity related to El Niño: when the ENSO index is greater than or equal to 1.7, it is deemed strong enough to cause capital destruction and (de-)anchoring of inflation expectations.

*The effect of the ENSO on GDP*

We adopt a structural interpretation of GDP decomposition into potential output and the output gap. GDP growth is decomposed as:

$$\Delta Y_t = y_t - y_{t-4} + \Delta Y_t^p \tag{4.1}$$

where $\Delta Y_t$ is interannual GDP growth, $y_t$ is the gap in production, and $\Delta Y_t^p$ is potential interannual GDP growth. The potential GDP corresponds to the level of production that the economy can reach given that the inflation is on its long term level. The potential GDP is supposed to be an exogenous process in our model. However, in the present of a extreme supply shock like a Strong El Niño, destruction of capital goods and lives happen, leading to a reduction of the level of product that can be sustained in the long term. Therefore, our specification for potential output, follows,

$$\Delta Y_t^p = (1 - \lambda^p)\Delta Y + \lambda^p \Delta Y_{t-1}^p + \Omega^{f/p} I_{(ICEN_t > 1.7)} ICEN_t + \epsilon_t^p \tag{4.2}$$

where $\Delta Y$ is the GDP growth rate in the steady state, $I_{(ICEN_t>1.7)}$ is a dummy variable that takes the value of one when $ICEN_t > 1.7$ and zero otherwise. Then, $\Omega^{f/p} ICEN_t$ captures the growth impact of El Niño on potential output growth, once $ICEN_t$ becomes bigger than two.

Regarding the effect of El Niño on the output gap, it occurs when the $ICEN_t > 1$. Thus, the dynamic of output gap, $y_t$, is determined by:

$$\begin{aligned} y_t = {} & a_y y_{t-1} + a_y^e \left( y_{t-1} + \Delta y_{t+1}^e \right) + a_\phi \phi_{t-1} + a_q q_t + a_g g_t + a_\tau \tau_t \\ & + a_{y^*} y_t^* + \Omega^{f/y} I_{(ICEN_t > 1)} ICEN_t + \epsilon_t^y \end{aligned} \tag{4.3}$$

where $\Delta y_t^e$ is economic agents' expectations regarding the output gap, which do not necessarily correspond with rational expectations, $\phi_t$ is a monetary condition index, $q_t$ is the real exchange rate gap, $g_t$ is the fiscal impulse, $\tau_t$ is the terms of trade impulse, $y_t^*$ is the gap in external output, $I_{(ICEN_t>1)}$ is a dummy variable that takes the value of one when $ICEN_t > 1$ and zero otherwise and $\epsilon_t^y$ is the aggregate demand shock. Analogously,

$\Omega^{f/y} ICEN_t$ captures the growth changes that El Niño causes on output gap when $ICEN_t$ is bigger than one.

*The effect of the ENSO on inflation*

Total inflation, $\pi_t$, is calculated as the aggregation of two components: inflation excluding food and energy, $\pi_t^{sae}$ and food and energy inflation: $\pi_t^{ae}$.

$$\pi_t = c_{sae}\pi_t^{sae} + (1 - c_{sae})\pi_t^{ae} \tag{4.4}$$

Food and energy inflation is modeled using two equations. The first one characterize it in the case when El Niño has no effect, i.e, $ICEN_t < 1$:

$$\pi_t^{ae} = (1 - \lambda_{ae}) \left[ b_s \pi_t^{sae} + (1 - b_s)\pi_t^m \right] + \epsilon_t^{ae} \tag{4.5}$$

In this equation, food and energy inflation is determined by core inflation (excluding food and energy) and imported inflation in domestic currency. The second equation describes the law of motion of food and energy inflation when El Niño occurs ($ICEN_t > 1$). It differs from the former by accounting i) a direct shift ($\Omega^{f/ae}$), and ii) an increase in persistence ($\lambda^{f/ae}$) due to changes in the ICEN index.

$$\pi_t^{ae} = (1 - \lambda_{ae}) \left[ b_s \pi_t^{sae} + (1 - b_s)\pi_t^m \right] + \lambda^{f/ae}\pi_{t-1}^{ae} + \Omega^{f/ae} ICEN_t + \epsilon_t^{ae}$$

We can encompass these two equations in one, by using the dummy variable $I_{(ICEN_t>1)}$, as we already did with the equations of potential GDP and the output gap:

$$\begin{aligned} \pi_t^{ae} &= (1 - \lambda_{ae}) \left[ b_s \pi_t^{sae} + (1 - b_s)\pi_t^m \right] \dots \\ &\quad \dots + \lambda^{f/ae} I_{(ICEN_t>1)} \pi_{t-1}^{ae} + \Omega^{f/ae} I_{(ICEN_t>1)} ICEN_t + \epsilon_t^{ae} \end{aligned} \tag{4.6}$$

In contrast, a standard Phillips curve still links core inflation (inflation excluding food and energy) with marginal cost which is determined by the output gap. The core inflation is not directly affected by El Niño shock, but only indirectly via inflation expectations.

The equation for forming inflation expectations includes both rational and adaptive components, where $E_t \Pi_{t+4}^{sae}$ is the rational expectation of core inflation (excluding food and energy four quarters in the future), $\Pi_t$ is the inflation trend, which is the average of current inflation and that of the previous three quarters, and $\epsilon_t^{\Pi^e}$ is the inflation shock to food and energy:

$$\Pi_t^e = \lambda_{\Pi^e}\Pi_{t-1}^e + (1 - \lambda_{\Pi^e}) \left[ (1 - c_p) E_t \Pi_{t+4}^{sae} + c_p \Pi_{t-1} \right] + \Omega^{f/exp} I_{(ICEN_{t-1}>2)} ICEN_t + \epsilon_t^{\Pi^e} \tag{4.7}$$

The direct transmission channel of El Niño shocks into inflation expectations is captured by term $\Omega^{f/exp} I_{(ICEN_t>1.7)} ICEN_t$. A ENSO shock only has an effect on inflation expectations when it becomes de-anchored, and we consider that will only happens when the economy is hit by a strongly high weather shock, i.e, when $ICEN_t > 1.7$.

### 4.2 Calibration

We calibrate the model to replicate some relevant unconditional and conditional moments for the Peruvian economy. We consider two set of parameters: the core set of parameters of the MPT as in Aguirre et al. (2022), and the set of parameters that govern the transmission of El Niño in the economy.

The first group of model's coefficients were estimated as in Aguirre et al. (2022) and set at the means of their posterior distributions. The coefficients introduced to extend the model to include climate change are estimated by using impulse response function matching estimators (IRFMEs), between those from LP and those obtained from the extended semi-structural model. We simulate an $ICEN$ shock and then compare with the impulse response of our Local Projection estimation but adapted to our quarterly model.The impact of the ENSO to the output gap was calibrated as a faction of the impact to the potential GDP.

The impulse response function matching for CPI inflation, inflation of food and energy, inflation expectations and GDP grow are displayed in 6. Blue lines marked with dots correspond to the point estimates. The shaded areas indicate 95 percent confidence intervals about the point estimates. The solid red lines pertain to the properties of our semi-structural model. To match the four empirical IRFs, we estimate four parameters: 1) the sensitivity of potential growth to the ENSO shock ($\Omega^{f/p}$), 2) the sensitivity of food and energy inflation to the ENSO shock ($\Omega^{f/ae}$), 3) the persistent of the inflation of food and energy ($\lambda^{f/ae}$) and, 4) the sensitivity of inflation expectations to the ENSO shock ($\Omega^{f/exp}$).

**Figure 6.** *IRF Matching*

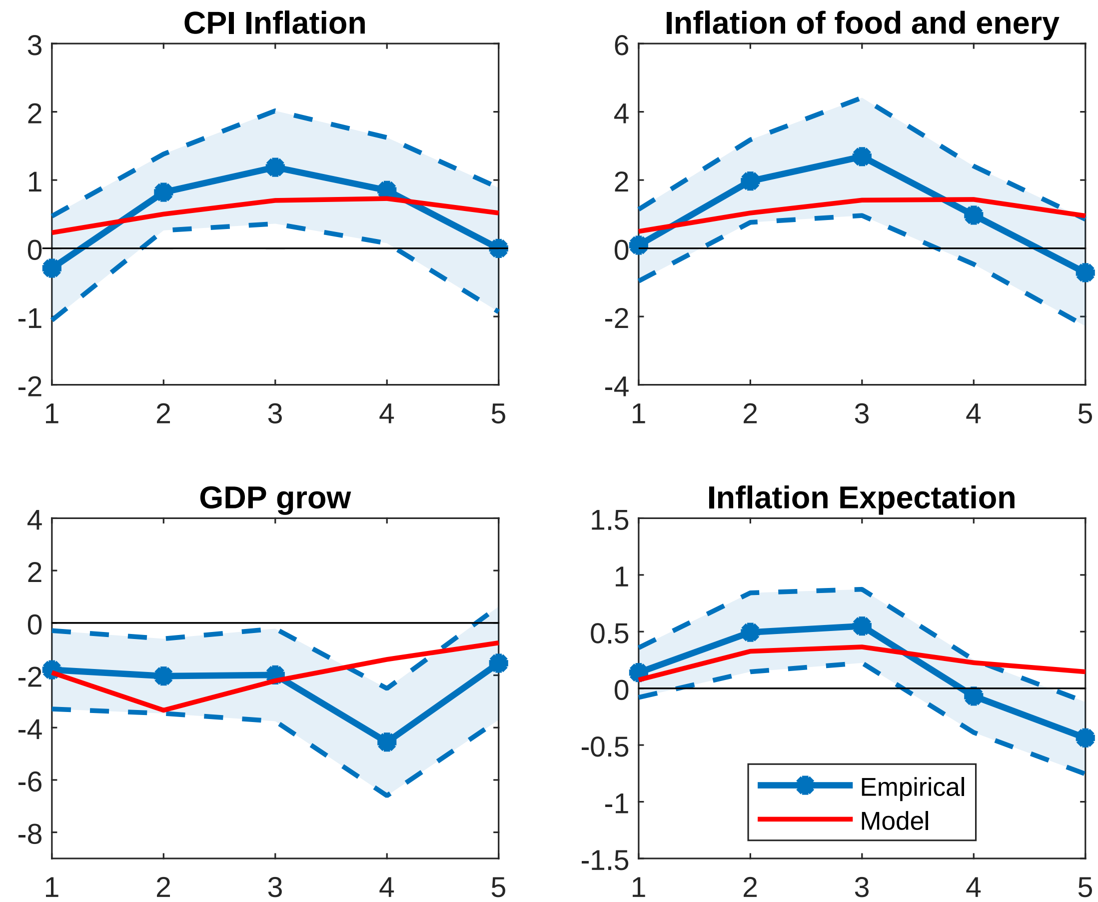


**Table 5.** *Parameters estimated by IRF Matching*

| | Parameters | Value |
|---|---|---|
| Potential GDP | $\Omega^{f/p}$ | -0.945 |
| Ouput Gap | $\Omega^{f/y}$ | -0.047 |
| Inflation Expectations | $\Omega^{f/exp}$ | 0.219 |
| Inflation of Food and Energy - Persistence | $\lambda^{f/ae}$ | 0.029 |
| Inflation of Food and Energy - Sensitivity | $\Omega^{f/ae}$ | 0.999 |

### 4.3 Results

Figure 7 shows the impulse responses of key macroeconomic variables following an ENSO shock, characterized by the ICEN index exceeding a value of 1.7. In other words, each panel pictures the temporal response of a macro variable after an El Niño event of category strong or more. This figure also presents two alternative parameterizations of the interest rate response to inflation deviations as represented in the Taylor curve, $\phi_\pi$. Given that the macroeconomic responses under these two alternatives are qualitatively similar, we first focus on the overall form of these responses before addressing the quantitative differences

In our model, El Niño operates through nonlinear mechanisms that lead to: (i) disruptions in economic activity by affecting both potential GDP and the output gap, and (ii) inflationary pressures through changes in food and energy prices as well as inflation expectations. Figure 7 illustrates that following the shock, GDP growth declines, and an initial increase in inflation that is largely driven by rising food and energy prices. This inflationary response becomes persistent, primarily due to the lagged adjustment in inflation expectations.

Interestingly, given the transmission mechanisms of El Niño in our model, it exerts a distinct behavior in the persistence of the negative effects on potential GDP and the output gap. The immediate and large drop of GDP growth mainly reflects the reaction of potential GDP growth, which returns to its previous growth rate after one quarter. In contrast, the output gap experiences a smaller initial decline but exhibits more persistent effects due to El Niño's spillover impacts on aggregate demand. Furthermore, the rise and shape of core inflation mirror the reaction of inflation expectations, producing a persistent effect of the ENSO shock on total inflation. To manage inflation and stabilize the economy, the central bank responds by raising the interest rate, in order to mitigate the inflationary pressures. This monetary tightening makes domestic assets more attractive to investors, leading to an appreciation of the exchange rate. The currency appreciation helps to mitigate the inflationary pressures by reducing the inflation of imported goods.

It is important to mention that the overall form of impulse responses to this shock resembles a cost-push shock as described by Woodford (2003), or relative price shocks as discussed by Aoki (2001); Del Negro et al. (2023). However, El Niño shock is distinct in that it exerts direct nonlinear effects on the output gap, potential GDP, and inflation expectations. These effects introduce unique challenges for the design of monetary policy.

To provide insights about the challenges faced by central banks in stabilizing both inflation and real economic activity, particularly given the breakdown of the "Divine Coincidence" (Woodford, 2003), we focus on an objective function that minimizes a weighted sum of the volatilities of inflation and the output gap. Specifically, we consider a loss function formulated as follows:

$$\mathcal{L} = \alpha\, var(y) + var(\pi)$$

where $\alpha \geq 0$ is the relative weight related to to fluctuations in the output gap.[3]

Table 6 provides a numerical illustration of the trade-off monetary policy faces, when stabilizing inflation and the output gap, after an ICEN shock (and only ICEN shocks). The table evaluates the loss function under different monetary policy stances, as captured by varying the sensitivity of the Taylor rule to inflation, $\phi_\pi$, and varying frequencies and magnitudes of El Niño events, represented by the variance of the ICEN shock, $\sigma^2_{ICEN}$. The table considers three values for the Taylor rule's inflation sensitivity parameter, $\phi_\pi = 1.2$, $\phi_\pi = 1.5$ (the baseline) and $\phi_\pi = 2$. A higher value indicates a more aggressive monetary policy response to inflation deviations. The ICEN shock standard deviation, $\sigma_{ICEN}$, reflects the intensity of the shock, with values set at 0.5, 1 (the baseline) and 2. These represent different frequencies and magnitudes of El Niño events. Each cell in the table represents the average outcome derived from $10^3$ simulations over a 20-year horizon, corresponding to the specified parameters settings.

**Table 6.** *Uncertainty, loss function and monetary policy stance*

| $\phi_\pi$ | 1.20 | | | 1.50 | | | 2.00 | | |
|---|---|---|---|---|---|---|---|---|---|
| $\sigma^2_{ENSO}$ | 0.50 | 1.00 | 2.00 | 0.50 | 1.00 | 2.00 | 0.50 | 1.00 | 2.00 |
| ENSO$>1$ | 1.23% | 8.05% | 15.61% | 1.23% | 8.05% | 15.61% | 1.23% | 8.05% | 15.61% |
| ENSO$>1.7$ | 0.02% | 2.30% | 10.05% | 0.02% | 2.30% | 10.05% | 0.02% | 2.30% | 10.05% |
| $\pi^{sae}$ | 0.016 | 0.111 | 0.375 | 0.016 | 0.106 | 0.347 | 0.016 | 0.100 | 0.315 |
| $\Pi^e$ | 0.004 | 0.095 | 0.405 | 0.003 | 0.090 | 0.377 | 0.003 | 0.083 | 0.344 |
| $\lambda$ | 0.010 | 0.100 | 0.404 | 0.010 | 0.105 | 0.431 | 0.011 | 0.113 | 0.469 |
| $\Lambda^e$ | 0.000 | 0.004 | 0.018 | 0.000 | 0.004 | 0.018 | 0.001 | 0.004 | 0.019 |
| $i$ | 0.007 | 0.073 | 0.292 | 0.007 | 0.076 | 0.312 | 0.008 | 0.082 | 0.339 |
| $rmc$ | 0.006 | 0.240 | 0.733 | 0.006 | 0.245 | 0.760 | 0.007 | 0.253 | 0.798 |
| $x$ | 0.006 | 0.059 | 0.171 | 0.006 | 0.060 | 0.174 | 0.006 | 0.061 | 0.180 |
| $\pi$ | 0.065 | 0.290 | 0.687 | 0.066 | 0.286 | 0.668 | 0.066 | 0.282 | 0.644 |
| $y$ | 0.014 | 0.146 | 0.439 | 0.013 | 0.149 | 0.454 | 0.013 | 0.152 | 0.474 |
| $\mathcal{L}$ | 0.004 | 0.085 | 0.481 | 0.004 | 0.083 | 0.456 | 0.004 | 0.081 | 0.426 |

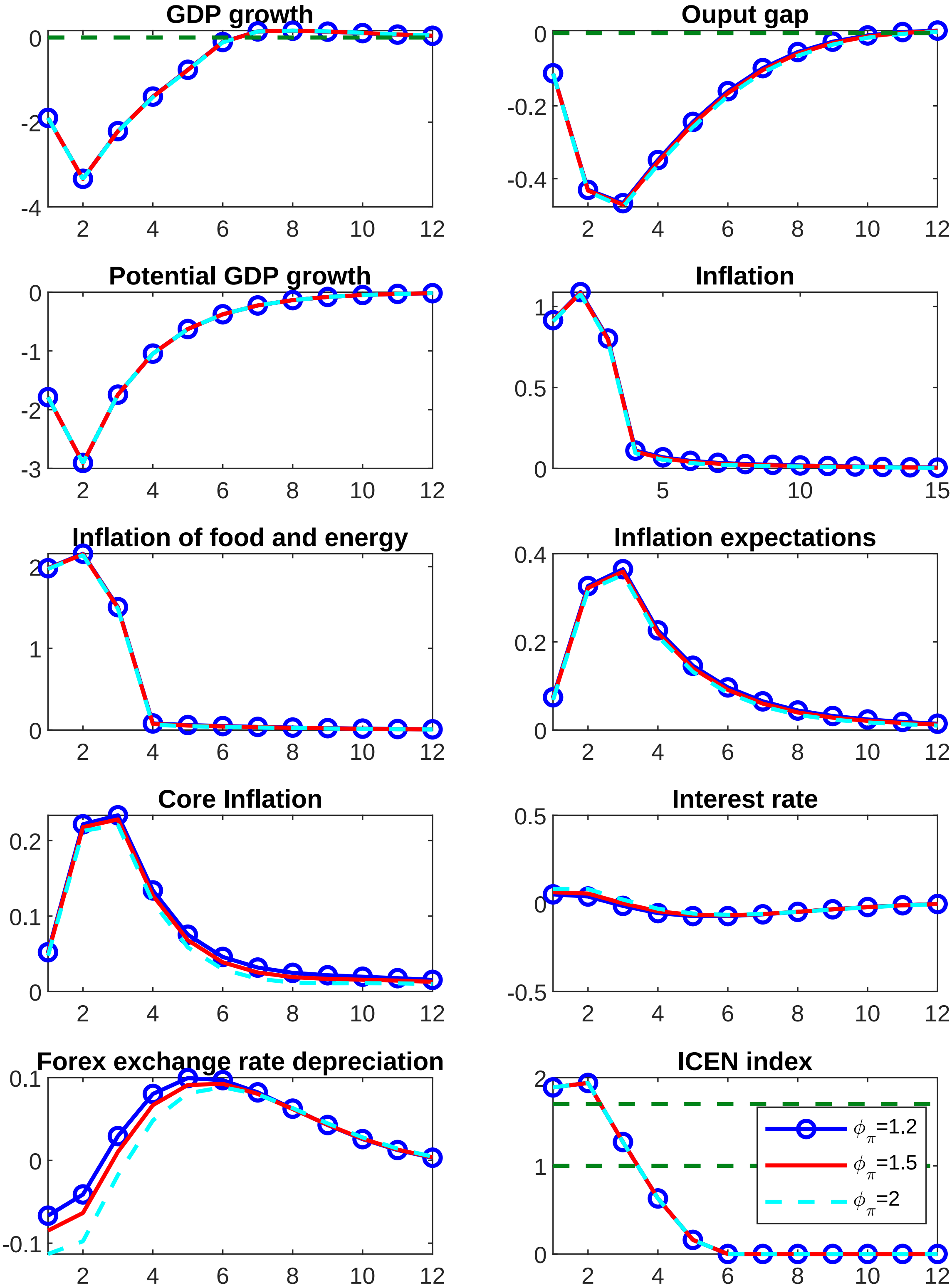
*Notes*: [a] The ENSO frequency is calibrated via $\sigma_{ICEN}$. The loss function, $\mathcal{L}$, is defined as a weighted sum of inflation and output gap volatility, $\alpha var(y) + var(\pi)$, with $\alpha = 0.048$ as in Woodford (2003). The variables $\pi$, $\pi^{sae}$, and $\Pi^e$ denote the annualized quarterly measures of the inflation rate, inflation excluding food and energy, and the 4-quarters ahead expected inflation, respectively. The nominal current and expected depreciation rates are $\lambda$ and $\Lambda^e$. The nominal interbank interest rate and the real marginal conditions are represented by $i$ and $rmc$, while $y$ is the output gap and $x$ represents the expected economic growth.

When the shock standard deviation is low ($\sigma_{ICEN} = 0.50$), the loss function value is close to 0 for all values of $\phi_\pi$, indicating no cost in stabilizing the economy. This result arises because, at low variance levels of the ICEN shocks, the frequency of El Niño events with a magnitude exceeding 1 is minimal (1.23 percent of the time), preventing the significant activation of nonlinear effects.

[3] This expression as described in Woodford (2003) can be motivated as the micro-founded welfare criterion for a central bank in the standard three equation NK model under certain assumptions. Following Woodford (2003) we set $\alpha = 0.048$

As the shock standard deviation increases to the baseline calibration ($\sigma_{ICEN} = 1.0$), the loss function rises for all values of $\phi_\pi$. This reflects a higher incidence of El Niño in the economy and its non-linear effects. For this calibration, the ENSO occurs on average 8.05% of the time (6 quarters out of 80) and it reaches strong ENSOs in 2.30% of the time (2 quarter out of 80). This frequency is sufficient to gauge significant welfare loss for all values of $\phi_\pi$. It can be seen in Table 6 that the variance of the key macroeconomic variables increase considerably. For instance, the volatility of nominal interes rate rises from 0.007 to 0.073 when $\phi_\pi = 1.2$, to 0.076 when $\phi_\pi = 1.5$, and from 0.008 to 0.082 when $\phi_\pi = 2.0$. Consequently, overall uncertainty in the economy increases substantially. As the utilized loss function is derived for a simple economy, it is probable that the welfare loss implied by the loss function is underestimated.

**Figure 7.** *Semi-Structural model: Effects of El Niño on the peruvian macroeconomy*




When the ICEN standard deviation doubles the baseline calibration ($\sigma_{ICEN} = 2$), the overall uncertainty of the economy and the loss function become remarkably larger. In this case, ENSO materializes 15.61% of the time (12 quarters out of 80) and reaches strong ENSOs 10.05% of the time (5 quarters out of 80). At this frequency, the loss function rises sharply, showing the largest increment when $\phi_\pi = 1.2$.

It can also be seen for this case, $\sigma_{ICEN} = 2$, that when the central bank is more reactive to the inflation rate (higher $\phi_{\pi}$), the loss function decreases. This reduction in the trade-off comes from the reduction of inflation volatility. This is also reflected in the volatility of inflation expectations, spot, and expected depreciation rates, which more than compensate for the rise in the volatility of variables related to economic activity. This result suggests that, in the face of significant supply shocks like ICEN, a stronger emphasis on controlling inflation might reduce economic instability.

However, it is important to note that stabilizing inflation may come at the cost of output gap stabilization. Figure 7 illustrates the impulse responses to a more aggressive monetary policy response following an El Niño event ($\phi_{\pi} = 1.5$). While inflation, core inflation, and inflation expectations exhibit a slightly smaller response compared to a less aggressive monetary stance, the differences are modest. In contrast, the output gap and foreign exchange depreciation show significantly more pronounced responses (consistent with Table $\sigma_{ICEN} = 2$). This highlights the unique challenges posed by the ICEN shock, with its direct nonlinear effects on the output gap, potential GDP, and inflation expectations, which complicates the design of effective monetary policy. These findings underscore the importance of carefully calibrating monetary policy to minimize the adverse impacts on both inflation and real economic activity.

## 5 Conclusion

We leverage on the exogeneity of El Niño and its significance for the Peruvian economy to investigate the impact of this climate shock on both inflation and output. Empirically and using a semi-structural model we show for the Peruvian economy that El Niño disrupts the conventional relationship between inflation and economic activity, akin to supply shocks.

The distinct nature of El Niño, with its direct nonlinear effects on the output gap, potential GDP, and inflation expectations, introduces additional complexities for monetary policy. Unlike typical cost-push shocks, the ICEN shock affects the economy through multiple channels, including potential GDP disruptions and persistent inflationary pressures. This necessitates a careful calibration of monetary policy to minimize the adverse impacts on both inflation and real economic activity. These complexities require a more nuanced approach to monetary policy, where traditional tools may need adjustment to effectively stabilize both inflation and economic activity.

Future research should focus on developing models that more accurately capture the impact of large climate shocks like El Niño and exploring how central banks can adapt their strategies to manage these unique challenges while ensuring economic stability. Our results indicate that hawkish monetary policy influences stabilization inflation dynamics following large supply shocks such as El Niño. However, the discussion remains open regarding the risks to central bank credibility when implementing more aggressive policies in response to supply shocks. Specifically, it is crucial to understand how deviations from expected policy paths might affect market perceptions and long-term trust in monetary authorities. In addition, it is important to analyze how repeated supply shocks might alter the effectiveness of traditional monetary policy tools and the consequent implementation of a hawkish policy response. Finally, it is important to design effective communication strategies to manage expectations and maintain credibility during periods of large shocks and strong policy tightening.

## Bibliography


Acevedo, S., Mrkaic, M., Novta, N., Pugacheva, E., and Topalova, P. (2020). The effects of weather shocks on economic activity: What are the channels of impact? *Journal of Macroeconomics*, 65:103207.

Aguirre, J., Arrieta, J., Castillo, L., Florian, D., Ledesma, A., Martinez, J., Morales, V., and Velez, A. (2022). Modelo de proyección trimestral: Una actualización hasta 2019. *Banco Central de Reserva del Perú*.

Alessandri, P. and Mumtaz, H. (2019). Financial regimes and uncertainty shocks. *Journal of Monetary Economics*, 101:31–46.

Amisano, G. and Giannini, C. (1997). *Topics in Structural VAR Econometrics*. Springer, 2nd rev. and enlarged ed. edition edition.

Aoki, K. (2001). Optimal monetary policy responses to relative-price changes. *Journal of Monetary Economics*, pages 55–80.

Auclert, A., Monnery, H., Rognlie, M., and Straub, L. (2023). Managing an energy shock: Fiscal and monetary policy. *National Bureau of Economic Research Working Paper Series*.

Banbura, M. and van Vlodrop, A. (2018). Forecasting with bayesian vector autoregressions with time variation in the mean. Tinbergen Institute Discussion Paper, No. TI 2018-025/IV.

Bandt, O., Rps Submitter, B. D. F., Jacolin, L., and Thibault, L. (2021). Climate change in developing countries : Global warming effects, transmission channels and adaptation policies. *SSRN Electronic Journal*.

Barnichon, R. and Brownlees, C. (2019). Impulse response estimation by smooth local projections. *The Review of Economics and Statistics*.

BCRP (1992). Memoria 1992.

BCRP (2014). Memoria 2014.

BCRP (2023). Memoria 2023.

Blanchard, O. and Gali, J. (2007). The macroeconomic effects of oil shocks: Why are the 2000s so different from the 1970s? *National Bureau of Economic Research Working Paper Series*.

Cai, W. and Santoso, A. (2023). New study helps solve a 30-year-old puzzle: how is climate change affecting el niño and la niña? *CSIRO*.

Callahan, C. and Mankin, J. (2023). Persistent effect of el niño on global economic growth. *Science*, 380.

Canova, F. and Pérez Forero, F. J. (2015). Estimating overidentified, nonrecursive, time-varying coefficients structural vector autoregressions. *Quantitative Economics*, 6:359–384.

Canova, F. and Pérez Forero, F. J. (2015). Estimating overidentified, nonrecursive, time-varying coefficients structural vector autoregressions: Estimating structural VARs. *Quantitative Economics*, 6(2):359–384.

Carriero, A., Clark, T. E., and Marcellino, M. (2016). Common drifting volatility in large bayesian vars. *Journal of Business and Economic Statistics*, 34(3):375–390.

Cashin, P., Mohaddes, K., and Raissi, M. (2016). El niño good boy or bad? *International Monetary Fund*.

CEPAL (2014). *La economía del cambio climático en el Perú*. CEPAL.

Chirinos, R. G. (2021). Efectos económicos del cambio climático en el perú. *Banco Central de Reserva del Perú*, No. 2021-009.

Ciccarelli, M. and Marotta, F. (2024). Demand or supply? an empirical exploration of the effects of climate change on the macroeconomy. *Energy Economics*, 129:107163.

Colacito, R., Hoffmann, B., and Phan, T. (2019). Temperature and growth: A panel analysis of the united states. *Journal of Money, Credit and Banking*, 51(2):313–368.

Cross, R. (2017). Changing the paradigm, acting faster el niño in peru.

Del Negro, M., Di Giovanni, J., and Dogra, K. (2023). Is the green transition inflationary? *SSRN Electronic Journal*.

Del Negro, M. and Primiceri, G. E. (2015). Time varying structural vector autoregressions and monetary policy: A corrigendum. *The Review of Economic Studies*, 82(4):1342–1345.

Dell, M., Jones, B. F., and Olken, B. A. (2012). Temperature shocks and economic growth: Evidence from the last half century. *American Economic Journal: Macroeconomics*, 4(3):66–95.

Faccia, D., Parker, M., and Stracca, L. (2021). Feeling the heat: Extreme temperatures and price stability. *SSRN Electronic Journal*.

Greenberg, N. (2023). El niño explained: Understanding the forces shaping 2023-24 winter weather. *Smithsonian National Museum of Natural History*.

Hsiang, S., Kopp, R., Jina, A., Rising, J., Delgado, M., Mohan, S., Rasmussen, D. J., Muir-Wood, R., Wilson, P., Oppenheimer, M., Larsen, K., and Houser, T. (2017). Estimating economic damage from climate change in the united states. *Science*, 356(6345):1362–1369.

Jordà, O. (2005). Estimation and inference of impulse responses by local projections. *American Economic Review*, 95(1):161–182.

Kim, H. S., Matthes, C., and Phan, T. (2021). Extreme weather and the macroeconomy. *Federal Reserve Bank of Richmond Working Papers*, 21(14):1–31.

Marticorena, B. (1999). Perú: Vulnerabilidad frente al cambio climático: Aproximaciones a la experiencia con el fenómeno el niño.

Mukherjee, K. and Ouattara, B. (2021). Climate and monetary policy: do temperature shocks lead to inflationary pressures? *Climatic Change*, 167(3):32.

Pozo, J. and Rojas, Y. (2024). The economic footprint of natural disasters: Demand-side or supply-side forces? *Mineo.*

Primiceri, G. (2005). Time varying structural vector autoregressions and monetary policy. *Review of Economic Studies*, 72:821–852.

Raissi, M., Cashin, P., and Mohaddes, K. (2015). *Fair weather or foul?: the macroeconomic effects of El Niño*. International Monetary Fund. OCLC: 908341871.

Ramey, V. A. and Zubairy, S. (2018). Government spending multipliers in good times and in bad: Evidence from US historical data. *Journal of Political Economy*, 126(2):850–901.

Ribes, A., Thao, S., and Cattiaux, J. (2020). Describing the relationship between a weather event and climate change: a new statistical approach. *Journal of Climate*, 33(15):6297–6314.

Rising, J. (2023). Loss and damage today: The uneven effects of climate change on global gdp & capital. *University of Delaware.*

Schnabel, I. (2022). A new age of energy inflation: climateflation, fossilflation and greenflation.

Senamhi (2014). El fenómeno el nino en el perú. *Institutional Report.*

Vargas, P. (2009). El cambio climático y sus efectos en el perú. *Working Paper Series, Banco Central de Reserva del Perú*, Working Paper Series.

Velarde, J. (2017). Reporte de inflación: Panorama actual y proyecciones macroeconómicas 2017-2019.

Woodford, M. (2003). *Interest and Prices: Foundations of a Theory of Monetary Policy.* Princeton, NJ: Princeton University Press.

# A Robustness to empirical results

Our analysis of the effects of El Niño on the Peruvian economy, using SLP impulse responses, captures the average impacts by aggregating all El Niño events. However, the intensity of specific El Niño events varies which lead to a range of economic impacts. Also, we consider a different technique, a Threshold BVAR to contrast our SLP results.

## A.1 Assessing the impact of the ENSO on GDP and Inflation: a TVP-VAR-SV approach

The intensity of specific El Niño events varies, which leads to a range of economic impacts. To gain insight into this temporal heterogeneity, we employ a Time-Varying Parameters Vector Autoregression with Stochastic Volatility (TVP-VAR-SV) approach to identify the effects of ICEN index shocks.

We consider a vector $y_t$ that includes the ICEN index along with key macroeconomic variables: headline inflation, economic activity index, terms of trade, interest rate, money aggregates, and exchange rate. The observed vector $y_t$ over a sample of $T$ periods, $t = 1, \ldots, T$, is assumed to be represented with a finite order autoregression:

$$y_t = B_{0,t}D_t + B_{1,t}y_{t-1} + \ldots + B_{p,t}y_{t-p} + u_t \tag{A.1}$$

where $B_{0,t}$ is a matrix of coefficients; $B_{i,t}, i = 1, \ldots, p$ are square matrices containing the coefficients of the lags of the the endogenous variables and $u_t \sim N(0, \Omega_t)$, where $\Omega_t$ is symmetric, positive, definite, and full rank for every $t$. The reduced form error $u_t$ does not have an economic interpretation. Structural shocks are denoted by $\varepsilon_t \sim N(0, I)$ and let the mapping between structural and reduced form shocks be:

$$u_t = A_t^{-1}\Sigma_t\varepsilon_t \tag{A.2}$$

where $A_t$ denotes the contemporaneous coefficients matrix and $\Sigma_t$ is a diagonal matrix containing the standard deviations of the structural shocks. The structural VAR($p$) model that correspond to the reduced VAR, in equation is (A.1):

$$y_t = X_t'B_t + A_t^{-1}\Sigma_t\varepsilon_t \tag{A.3}$$

where $X_t' = I_M \otimes [D_t', y_{t-1}', \ldots, y_{t-k}']$ and $B_t = [\text{vec}(B_{0,t})', \text{vec}(B_{1,t})', \ldots, \text{vec}(B_{p,t})']'$. As is standard in the literature, we assume that the parameter blocks $(B_t, A_t, \Sigma_t)$ evolve as independent random-walks:

$$\begin{aligned} B_t &= B_{t-1} + \nu_t \\ \alpha_t &= \alpha_{t-1} + \zeta_t \\ \log(\sigma_t) &= \log(\sigma_{t-1}) + \eta_t \end{aligned}$$

where $\alpha_t$ denotes the vector of free parameters of $A_t$, and $\sigma_t = \text{diag}(\Sigma_t)$, where stochastic vectors $\varepsilon_t, \nu_t, \zeta_t, \eta_t$ are orthogonal.

This setup is able to capture time variations in i) the lag structure, ii) the contemporaneous reaction parameters, and iii) the structural variances. This method allows us to compute impulse responses at each point in time, providing a dynamic perspective on the economic effects of El Niño shocks. By doing so, we can better understand how the impacts of El Niño have evolved. This approach is also particularly valuable in guiding our understanding of the uncertainty and potential future effects of more frequent and intense El Niño events.

We estimate the TVP-VAR-SV model in equation (A.3) for the sample period between December 1994 and March 2024. We use the methodology proposed by Canova and Pérez Forero (2015), with the correction made by Del Negro and Primiceri (2015).

### A.2 A Threshold BVAR approach

We specify the following two-regime Vector Auto-Regressive model (Threshold-BVAR), which closely follows Alessandri and Mumtaz (2019):

$$\begin{aligned} y_t = &\left(c_1 + \sum_{j=1}^{p} \beta_{1,j} y_{t-j} + \sum_{j=0}^{J} \gamma_{1,j} \lambda_{t-j} + \Omega_{1t}^{1/2} \varepsilon_t\right) \tilde{S}_t + \\ &\left(c_2 + \sum_{j=1}^{p} \beta_{2,j} y_{t-j} + \sum_{j=0}^{J} \gamma_{2,j} \lambda_{t-j} + \Omega_{2t}^{1/2} \varepsilon_t\right) \left(1 - \tilde{S}_t\right) \end{aligned} \tag{A.4}$$

where the vector of variables $y_t$ is the same as in the previous model, and where the shocks are normally distributed, i.e., $e_t \sim i.i.d.N\left(0, I_{dim(y)}\right)$.

The binary regime indicator $\tilde{S}_t$ is defined by:

$$\tilde{S}_t = 1 \iff F_{t-d} \leq Z^* \tag{A.5}$$

and where both the delay $d$ (which follows a discrete distribution $d = 1, \ldots, d^*$), and the threshold $Z^*$, are unknown parameters that need to be estimated. Moreover, we employ as a threshold variable $F_t$, the ICEN indicator.

The covariance matrix for the error term $\Omega_{it}^{1/2} e_t$ for each regime $i = 1, 2$ is such that:

$$\Omega_{1t} = A_1^{-1} \Sigma_t A_1^{-1\prime} \tag{A.6}$$

$$\Omega_{2t} = A_2^{-1} \Sigma_t A_2^{-1\prime} \tag{A.7}$$

with $A_i$ as a lower triangular matrix and $\Sigma_t$ as a matrix defined by:

$$\Sigma_t = exp\left(\lambda_t\right) \times S \tag{A.8}$$

with $S$ being a diagonal matrix that captures the constant heteroskedasticity:

$$S = \begin{bmatrix} s_1 & 0 & \ldots & 0 \\ 0 & s_2 & \ldots & 0 \\ \ldots & \ldots & \ldots & \ldots \\ 0 & 0 & \ldots & s_{dim(y)} \end{bmatrix} \tag{A.9}$$

with $s_j > 0$ for $j = 1, \ldots, dim\left(y\right)$. The matrices $A_i$ are lower triangular with the main diagonal governed by ones and free parameters below the main diagonal, i.e.:

$$A = \begin{bmatrix} 1 & 0 & \ldots & 0 \\ \alpha_{i,1} & 1 & \ldots & 0 \\ \ldots & \ldots & \ldots & \ldots \\ \alpha_{i,k} & \alpha_{i,k+1} & \ldots & 1 \end{bmatrix}. \tag{A.10}$$

In this context, also recall that $vec(A_i) = S_A \alpha_i + s_A$ (Amisano and Giannini, 1997), with $S_A$ and $s_A$, are matrices governed by 0s and 1s. The latter is a useful transformation in order to sample the full parameter of vector $\alpha$ (Canova and Pérez Forero, 2015).

Finally, log-volatility $\lambda_t$ enters both in the mean (with lags) and in the covariance matrix $\Omega_t$. The log-volatility component can also be interpreted as an uncertainty measure, which can be represented as a stationary $AR(1)$ process with drift:

$$\lambda_t = \mu + F(\lambda_{t-1} - \mu) + \eta_t \tag{A.11}$$

with $0 < F < 1$ and $\eta_t \sim i.i.d.N(0, Q)$. A single scalar process governs the time varying volatility (Carriero et al., 2016; Alessandri and Mumtaz, 2019), which is a more parsimonious representation than other specifications where each shock has a different time dependent variance (Primiceri (2005), Canova and Pérez Forero (2015), (Banbura and van Vlodrop, 2018)).

The posterior distribution is computed using standard Markov Chain Monte Carlo methods, and in this case the parameter space $\Theta$ is such that $\Theta = \{\beta, \gamma, \alpha, \lambda^T, S, \mu, F, Q\}$, plus the variances of the transition equations.

The impulse response functions should be computed as the difference of two forecasts such that:

$$\frac{\partial y_{t+h}}{\partial u_t} = E(y_{t+h} \mid \Theta, \delta) - E(y_{t+h} \mid \Theta), \qquad h = 0, 1, \ldots, \overline{H} \tag{A.12}$$

Note that in the threshold model, the shock could trigger a regime switch. Therefore, in this case, it is even more crucial to consider these two forecasts instead of relying on a static power matrix formula.

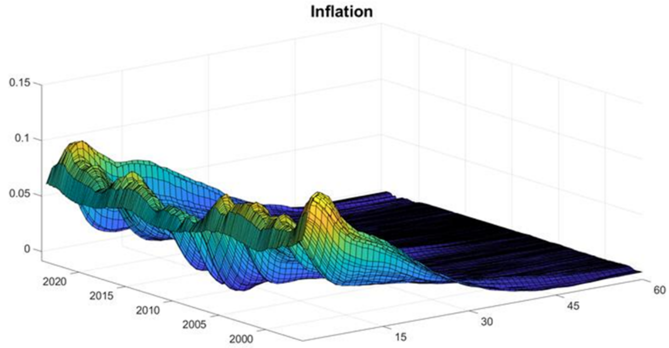
#### Results

Figure 8 illustrates the impulse responses of inflation and economic activity to a shock in the ICEN Index over time, as computed using a Time-Varying Vector Autoregressive model with Stochastic Volatility (TVP-VAR-SV). Each panel presents the surface plot which demonstrates how these responses evolved following a shock. The y-axis represents percentage changes, the x-axis corresponds to the time period of the sample, and the z-axis indicates the number of months after the shock. At any point along the x-axis on the surface plot, lines extending across the z and x axes depict the median estimated values over time. Overall, the responses exhibit significant variation across periods, indicating that the impact of the ICEN Index shocks on inflation is dynamic and evolves over time.

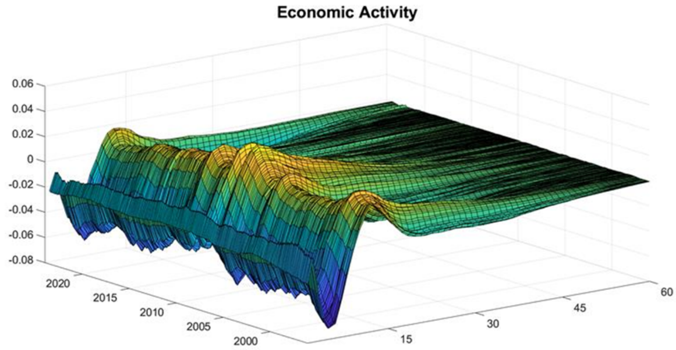
In panel A and B of Figure 8, the surface plots show how the impulse responses of inflation and economic activity evolved over time following a shock in the ICEN Index. It is generally observed that positive temperature shocks cause an increase in inflation and contraction in GDP over time. The most pronounced responses correlate with severe El Niño episodes, specifically those in 1998, 2017, and most recently, 2022-2023.

**Figure 8.** *TVP-VAR-SV: ICEN shock and median value responses of inflation and economic activity (1995-2023)*

Panel A



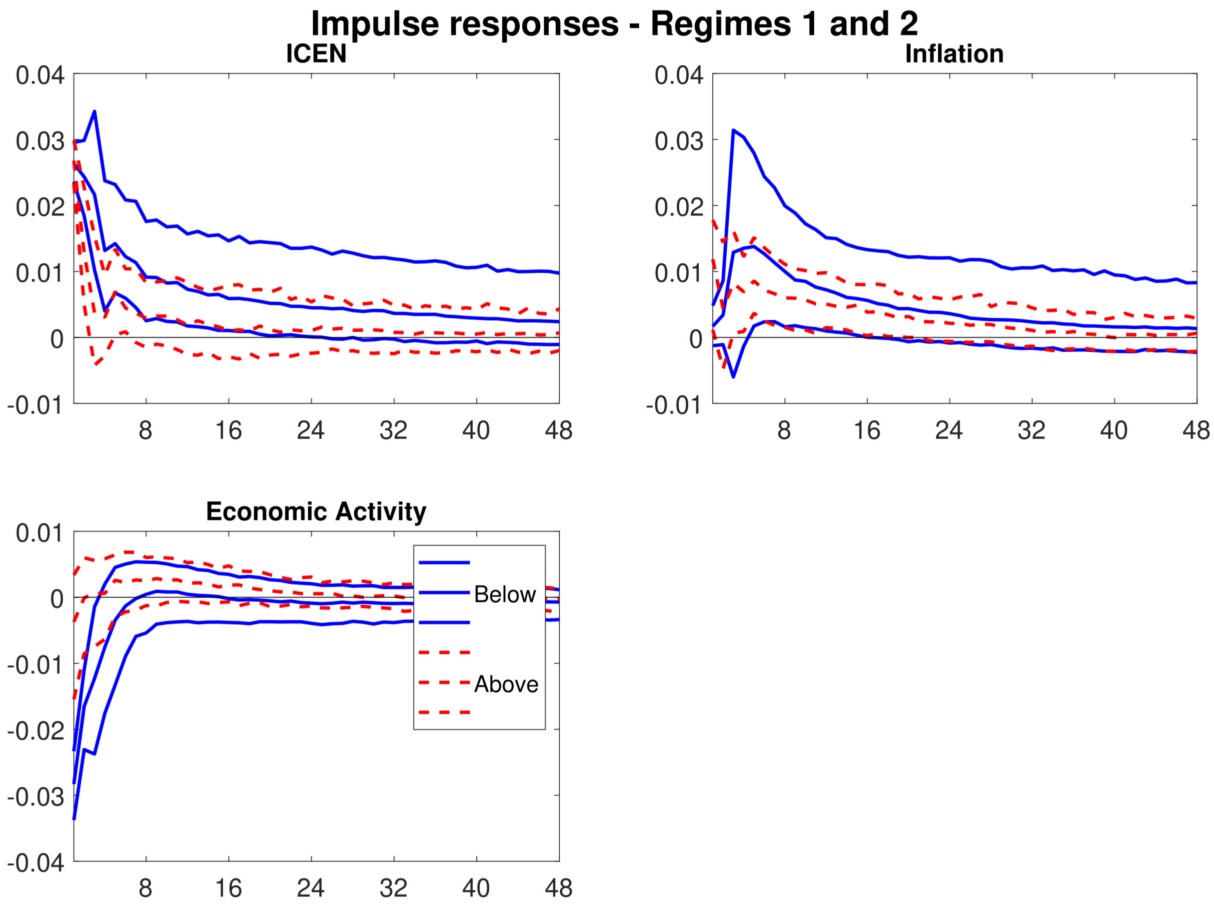

Panel B




*Note*: TVP-VAR-SV impulse responses of macroeconomic variables to a one-degree change in temperature (i.e., a one-unit increase in the ICEN Index). The y-axis represents percentage changes, the x-axis represents the time period of the sample, and the z-axis indicates the number of months after the shock. At any given point on the x-axis, the lines show the median estimated values at that time.

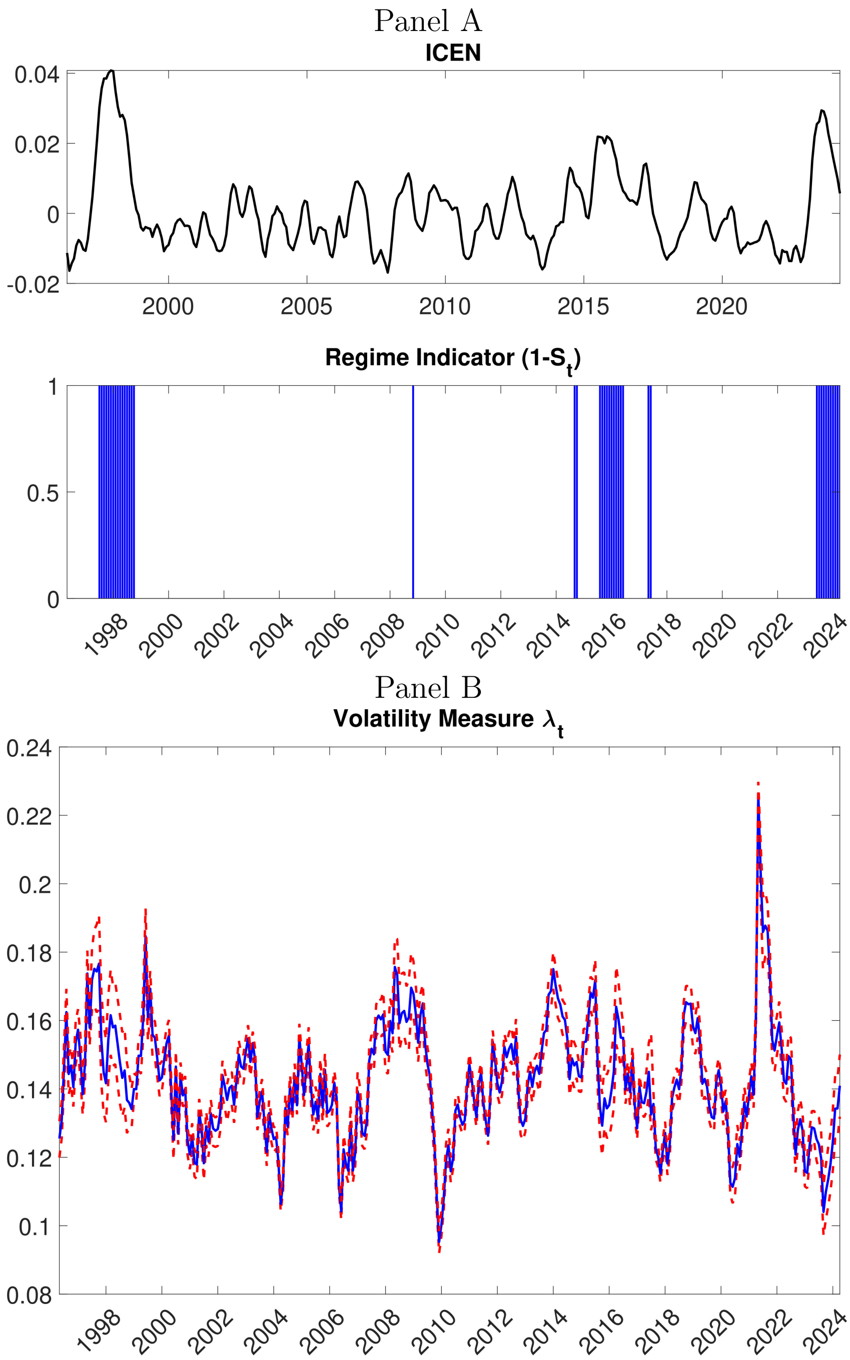
Figure 9 illustrates the impulse responses within the Threshold BVAR model. We find that there are potential differences in the responses to shocks in the ICEN variable, depending on whether the initial conditions are below or above the threshold. Notably, because the model is nonlinear, shocks starting below the threshold tend to be more amplified, potentially triggering a regime switch within the forecast horizon.

**Figure 9.** *Threshold-BVAR-SV: ICEN shock and median value responses of inflation and economic activity)*



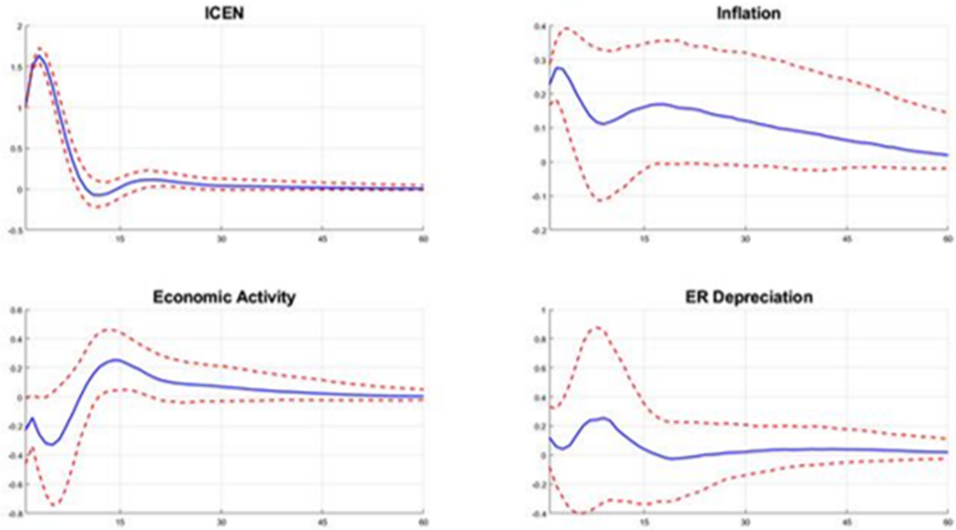

In addition, the model identifies regime switches for temperatures above 1 on the ICEN index, as it is depicted by Figure 10, panel A. The identified periods coincide with the dates when the El Niño phenomenon manifested most intensely. We also control for Stochastic Volatility in means, a very useful component when working with data that has outliers, such as the period associated with the COVID-19 pandemic (see panel B).

**Figure 10.** *Threshold-BVAR-SV: Estimated ICEN Regimes and Volatility Component*




To demonstrate the effects of severe temperature variations similar to an El Niño shock through the lens of the TVP-VAR-SV model, Figure 11 depicts the median impulse responses and 68% confidence intervals following the ICEN shock in 1998. The median impulse responses show that the 1998 El Niño event initially caused a decrease in GDP of approximately 20 bps, accompanied by a rise in headline inflation of about 22 bps. The effect was temporary for economic activity but more persistent for inflation. The economic response became statistically insignificant approximately six months following the shock, but the inflationary effects were still present 15 months after the shock. It is important to note that there is uncertainty about the effect's size and direction, as indicated by wider confidence intervals. Specifically, the negative GDP impact may have been larger. These results are consistent with our estimates using SLP impulse responses in Section 3.3, in terms of direction, size, and persistence.

**Figure 11.** *TVP-VAR-SV: ICEN shock and El Niño 1998*




*Note*: TVP-VAR-SV impulse responses of macroeconomic variables to a one-degree change in temperature (i.e., a one-unit increase in the ICEN Index) in 1998Q3. The y-axis represents percentage changes, the x-axis indicates the number of months after the shock. The blue line represents the median value and red lines are the 68% confidence intervals.

# B Semi-Structural nonlinear Model

## B.1 The model

### The ENSO index

$$ICEN_t = \lambda^f ICEN_{t-1} + \epsilon_t^f, \qquad \epsilon_t^f \sim N(0, \sigma_f^2) \tag{B.1}$$

### GDP Growth and Potential GDP Growth

$$\Delta Y_t = y_t - y_{t-4} + \Delta Y_t^p \tag{B.2}$$

$$\Delta Y_t^p = (1-\lambda^p)\Delta Y + \lambda^p \Delta Y_{t-1}^p + \Omega^{f/p} I_{(ICEN_t>1.7)} ICEN_t + \varepsilon_t \tag{B.3}$$

### Inflation

$$\pi_t^{sae} = b_m \Pi_t^m + (1-b_m)\left[b_{sae}\pi_{t-1}^{sae} + (1-b_{sae})\Pi_t^e\right] + b_y y_{t-1} + \varepsilon_t \tag{B.4}$$

$$\Pi_t^{sae} = (\pi_t^{sae} + \pi_{t-1}^{sae} + \pi_{t-2}^{sae} + \pi_{t-3}^{sae})/4 \tag{B.5}$$

$$\pi_t^{ae} = b_s\pi_t^{sae} + (1-b_s)\pi_t^m + (\lambda^{f/ae}\pi_{t-1}^{ae} + \Omega^{f/ae})I_{(ICEN_t>1)}ICEN_t + \varepsilon_t \tag{B.6}$$

$$\Pi_t^{ae} = (\pi_t^{ae} + \pi_{t-1}^{ae} + \pi_{t-2}^{ae} + \pi_{t-3}^{ae})/4 \tag{B.7}$$

$$\pi_t = c_{sae}\pi_t^{sae} + (1-c_{sae})\pi_t^{ae} \tag{B.8}$$

$$\Pi_t = (\pi_t + \pi_{t-1} + \pi_{t-2} + \pi_{t-3})/4 \tag{B.9}$$

$$\begin{aligned}\Pi_t^e &= \lambda_{\Pi^e}\Pi_{t-1}^e + (1-\lambda_{\Pi^e})\left[(1-c_p)E_t\Pi_{t+4}^{sae} + c_p\Pi_{t-1}\right] + \ldots \\ &\quad \ldots + \Omega^{f/exp}I_{(ICEN_{t-1}>1.7)}ICEN_t + \varepsilon_t\end{aligned} \tag{B.10}$$

$$\widehat{\Pi}_t = E_t\Pi_{t+4}^{sae} - Meta \tag{B.11}$$

$$\pi_t^m = c_{mm}\pi_{t-1}^m + (1-c_{mm})E_t\Pi_{t+4}^m + c_{mq}\left[\pi_{t-1}^{m\$} + \lambda_{t-1} - \pi_{t-1}^m\right] + \varepsilon_t \tag{B.12}$$

$$\Pi_t^m = (\pi_t^m + \pi_{t-1}^m + \pi_{t-2}^m + \pi_{t-3}^m)/4 \tag{B.13}$$

**Interest rates in local currency**

$$i_t = \rho_i i_{t-1} + (1-\rho_i)\left[i_t^n + f_\pi\widehat{\Pi}_t + f_y\left[c_{fy}y_t + (1-c_{fy})y_{t-1}\right]\right] + \varepsilon_t \tag{B.14}$$

$$i_t^n = (1-\rho_{i^n})i + \rho_{i^n}i_{t-1}^n + \varepsilon_t \tag{B.15}$$

$$i_t^{mn} = i_t + \varepsilon_t \tag{B.16}$$

$$R_t^{mn} = i_t^{mn} - \Pi_t^e \tag{B.17}$$

$$R_t^{mn/eq} = Z_t^{mn} + cY_{mn}\left[\Delta Y_{t+1}^p - \Delta Y\right] + cR_{mn}\left[\Delta Y_{t+1}^{*/p} - \Delta Y^*\right] + \varepsilon_t \tag{B.18}$$

$$Z_t^{mn} = c_{zmn}Z_{t-1}^{mn} + (1-c_{zmn})R^{mn} + \varepsilon_t \tag{B.19}$$

$$r_t^{mn} = R_t^{mn} - R_t^{mn/eq} \tag{B.20}$$

(B.21)

**Interest rates in foreign currency**

$$i_t^{me} = i_t^* + \varepsilon_t \tag{B.22}$$

$$R_t^{me} = i_t^{me} - \Pi_t^e + \Lambda_t^e \tag{B.23}$$

$$R_t^{me/eq} = Z_t^{me} + cY_{me}\left[\Delta Y_{t+1}^p - \Delta Y\right] + cR_{me}\left[\Delta Y_{t+1}^{*/p} - \Delta Y^*\right] + \varepsilon_t \tag{B.24}$$

$$Z_t^{me} = c_{zme} Z_{t-1}^{me} + (1 - c_{zme})\, R^{me} + \varepsilon_t \tag{B.25}$$

$$r_t^{me} = R_t^{me} - R_t^{me/eq} \tag{B.26}$$

$$\tag{B.27}$$

**Exchange Rate**

$$\lambda_t = \rho_\lambda E_t \lambda_{t+1} + (1 + \rho_\lambda)\left[i_t^{me} + \xi_t - i_t^{mn} + \varepsilon_t\right] \tag{B.28}$$

$$\Lambda_t = (\lambda_t + \lambda_{t-1} + \lambda_{t-2} + \lambda_{t-3})/4 \tag{B.29}$$

$$\Lambda_t^e = \rho_{\lambda^e} \Lambda_{t-1}^e + (1 - \rho_{\lambda^e})\Lambda_{t+4} + \varepsilon_t \tag{B.30}$$

$$\xi_t = \xi_t^{eq} + \varepsilon_t \tag{B.31}$$

$$\xi_t^{eq} = (1 - \rho_\xi)\xi + \rho_\xi \xi_{t-1}^{eq} + \varepsilon_t \tag{B.32}$$

$$Q_t = \pi_t^* + \lambda_t - \pi_t \tag{B.33}$$

$$q_t = q_{t-1} + \frac{Q_t - Q_t^{eq}}{4} \tag{B.34}$$

$$Q_t^{eq} = \rho_Q q_t + \varepsilon_t \tag{B.35}$$

**Output gap and its determinants**

$$\begin{aligned} y_t = {} & a_{y^e}\left[x_t^e + y_{t-1}\right] + a_y y_{t-1} + a_\psi \psi_{t-1} + a_\tau \tau_t + a_q q_t + a_{y^*} y_t^* + \ldots \\ & a_t t_t + a_g g_t + \Omega^{f/y} I_{(ICEN_t > 1)} ICEN_t + \varepsilon_t \end{aligned} \tag{B.36}$$

$$x_t^e = \rho_{x^e} x_{t-1}^e + (1 - \rho_{x^e})\left[E_t y_{t+1} - y_{t-1}\right] + \varepsilon_t \tag{B.37}$$

$$\psi_t = -\left[c_r^{mn} r_t^{mn} + c_r^{me} r_t^{me} + c_{hb}(\xi_t - \xi_t^{eq})\right] \tag{B.38}$$

$$t_t = \rho_t t_{t-1} + \varepsilon_t \tag{B.39}$$

$$g_t = \rho_g g_{t-1} + \varepsilon_t \tag{B.40}$$

$$T_t = \rho_T T_{t-1} + \varepsilon_t \tag{B.41}$$

$$\tau_t = (a_{\tau_{largo}} + a_{\tau_{corto}})\tau_{t-1} - a_{\tau_{largo}} a_{\tau_{corto}} \tau_{t-2} + (a_{\tau_{largo}} - a_{\tau_{corto}})\frac{T_t}{4} + \varepsilon_t \tag{B.42}$$

$$\tag{B.43}$$

**Foreign economy**

$$\pi_t^* = b_\pi^* \pi_{t-1}^* + (1 - b_\pi^*) E_t \Pi_{t+4}^* + b_y^* y_{t-1}^* + \varepsilon_t \tag{B.44}$$

$$\Pi_t^* = (\pi_t^* + \pi_{t-1}^* + \pi_{t-2}^* + \pi_{t-3}^*)/4 \tag{B.45}$$

$$\pi_t^{m\$} = (1 - c_{\pi^{m\$}})\pi_t^{*\$} + c_{\pi^{m\$}} \pi_{t-1}^{*\$} + \varepsilon_t \tag{B.46}$$

$$i_t^* = \rho_i^* i_{t-1}^* + (1 - \rho_i^*) \left[ i_t^{*n} + f_\pi^* (E_t \Pi_{t+4}^* - \pi^*) + f_y^* y_t^* \right] + \varepsilon_t \tag{B.47}$$

$$i_t^{*n} = (1 - \rho_{i^n}) i^* + \rho_{i^n} i_{t-1}^{*n} + \varepsilon_t \tag{B.48}$$

$$R_t^* = i_t^* - \Pi_{t+4}^* \tag{B.49}$$

$$R_t^{*/eq} = Z_t^* + cY^* \left[ \Delta Y_{t+1}^{*/p} - \Delta Y^* \right] \tag{B.50}$$

$$Z_t^* = (1 - \rho_{Z^*}) R^* + \rho_{Z^*} Z_{t-1}^* + \varepsilon_t \tag{B.51}$$

$$r_t^* = R_t^* - R_t^{*/eq} \tag{B.52}$$

$$\Delta Y_t^* = y_t^* - y_{t-4}^* + \Delta Y_t^{*/p} \tag{B.53}$$

$$\Delta Y_t^{*/p} = (1 - \rho_{\Delta Y^{*/p}}) \Delta Y^* + \rho_{\Delta Y^{*/p}} \Delta Y_{t-1}^{*/p} + \varepsilon_t \tag{B.54}$$

$$y_t^* = a_{Ey}^* y_{t+1}^* + a_y^* y_{t-1}^* - a_r^* r_{t-1}^* + \varepsilon_t \tag{B.55}$$

## C Bias in Local Projection

For simplicity, assume a local projection regression without the non-linear feature in Section 3.3, that is,

$$y_{t+h} = a_h + \gamma_h x_t + B_h X_t + e_{t+h} \tag{C.1}$$

where the control variable $X$ may include lags of $x$. Consider $x$ to be persistent (as the ICEN); hence, it can be modeled as an AR process. Assume $x \sim AR(p)$. That is,

$$x_t = \rho_0 + \sum_{i=1}^{p} \rho_i x_{t-i} + \varepsilon_t. \tag{C.2}$$

From this autocorrelation equation, the population equation for $y_{t+h}$ should look something like

$$y_{t+h} = a_h + \gamma_h x_t + B_h X_t + \ldots + \underbrace{\sum_{i=1}^{h} c_i E_t x_{t+i} + v_{t+h}}_{e_{t+h}}. \tag{C.3}$$

As a result, $x_t$ is endogenous since $\text{cov}(x_t, e_{t+h}) = \sum_{i=1}^{h} c_i \text{cov}(x_t, E_t x_{t+h}) \neq 0$. From C.2, the contribution to $E_t x_{t+j}$ from $x_t$ can be calculated as

$$\frac{\partial E_t x_{t+j}}{\partial x_t} = \varrho_j; \text{ hence, } E_t x_{t+j} = \varrho_j x_t + \ldots,$$

for instance, $\varrho_j = \rho_1^j$ in the case of an $AR(1)$ process. Adding the regressor $E_t x_{t+j}$ in C.1 yields

$$y_{t+h} = a_h + \left(\gamma_h + \sum_{i=1}^{h} c_i \varrho_i\right) x_t + B_h X_t + e_{t+h}. \tag{C.4}$$

If $\hat{\gamma}_h$ comes from the estimation of C.1, from C.4 it is known that $\hat{\gamma}_h = \gamma_h + \sum_{i=1}^{h} c_i \varrho_i$. As a result, the bias is $\sum_{i=1}^{h} c_i \varrho_i$. This bias is expected to be negative as $c_i < 0$ (note that $c_i$ is unknown). Consequently, the estimation will be downward biased. The solution to this problem is to replace $x$ with the OLS estimate of $\varepsilon$ in C.2 as it is an i.i.d. process.

Now let's address the non-linearity. To do so, the indicator function is added to identify the ENFEN state, which occurs when $x_t > 1$. That is,

$$\begin{aligned} y_{t+h} =& \mathcal{I}(x_{t-1} > 1) \left[a_{1,h} + \gamma_{1,h} \hat{\varepsilon}_t + B_{1,h} X_t + e_{1,t+h}\right] \\ &+ (1 - \mathcal{I}(x_{t-1} > 1)) \left[a_{2,h} + \gamma_{2,h} \hat{\varepsilon}_t + B_{2,h} X_t + e_{2,t+h}\right], \end{aligned} \tag{C.5}$$

notice that the indicator function is lagged rather than contemporaneous. This lag structure is used to ensure exogeneity. To see this, note that C.5 can be written as

$$\begin{aligned} y_{t+h} =& \gamma_{2,h} \hat{\varepsilon}_t + (\gamma_{1,h} - \gamma_{2,h}) \mathcal{I}(x_{t-1} > 1) \hat{\varepsilon}_t \\ &+ \mathcal{I}(x_{t-1} > 1) \left[a_{1,h} + B_{1,h} X_t + e_{1,t+h}\right] \\ &+ (1 - \mathcal{I}(x_t > 1)) \left[a_{2,h} + B_{2,h} X_t + e_{2,t+h}\right]. \end{aligned} \tag{C.6}$$

As $\hat{\varepsilon}_t$ is exogenous, the estimation of $\gamma_{2,h}$ is consistent. With a similar argument as in the linear case, the regressor $\mathcal{I}(x_{t-1} > 1)\hat{\varepsilon}_t$ must be uncorrelated with the omitted variable

$E_t\mathcal{I}(x_{t+j-1} > 1)\hat{\varepsilon}_{t+j}$ in C.6. As $\hat{\varepsilon}_{t+j}$ is orthogonal to $x_{t+j-1}$, then $E_t\mathcal{I}(x_{t+j-1} > 1)\hat{\varepsilon}_{t+j} = 0$, which implies the required exogeneity.

A consequence of the lag structure is that the ENFEN effects, $\{\gamma_{1,h}\}_{h\leq H}$, can be estimated only one month after the event materializes.

$$\frac{\partial y_{t+h}}{\partial \varepsilon_t} = \gamma_{2,h} + (\gamma_{1,h} - \gamma_{2,h})\mathcal{I}(x_{t-1} > 1) = \begin{cases} \gamma_{2,h}, & \text{if } x_{t-1} < 1 \\ \gamma_{1,h}, & \text{if } x_{t-1} > 1 \end{cases} \tag{C.7}$$