BIS Working Papers
No 1276

Economic activity, inflation, and monetary policy after extreme weather events: ENSO and its economic impact on the Peruvian economy

by John Aguirre, Alan Ledesma, Fernando Perez and Youel Rojas

Monetary and Economic Department

July 2025

JEL classification: E31, E52, O44, Q54

Keywords: climate, extreme weather events, growth, inflation, financial and macroeconomic stability

BIS Working Papers are written by members of the Monetary and Economic Department of the Bank for International Settlements, and from time to time by other economists, and are published by the Bank. The papers are on subjects of topical interest and are technical in character. The views expressed in them are those of their authors and not necessarily the views of the BIS.

This publication is available on the BIS website (www.bis.org).

ISSN 1020-0959 (print)
ISSN 1682-7678 (online)

Economic Activity, Inflation, and Monetary Policy after Extreme Weather Events: ENSO and its Economic Impact on the Peruvian Economy

John Aguirre* Alan Ledesma† Fernando Perez‡ Youel Rojas§

Version:
July, 2025

Abstract

This paper studies how El Niño Costero, a large climatic event, generates physical risks disrupting business cycles and hindering the effectiveness of monetary policy. Using Peruvian data, we find consistent empirical evidence that El Niño shocks leave a footprint on the economy akin to a supply-side shock: it exerts inflationary pressures while simultaneously contracting GDP. The effects are very persistent and reflect the differentiated effects across sectors in the economy. Primary sectors response is more immediate and larger but persistent. Conversely, non-primary sectors experience lagged effects that become considerably more persistent and important later on. We integrate these empirical findings into a semi-structural model that incorporates five non-linear transmission channels through which El Niño affects the economy. These non-linearities present 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. Faced with such large-scale shocks, hawkish conventional monetary policy remains a relevant, though limited, tool for stabilizing inflation dynamics.

Keywords: Climate, Extreme Weather Events, Growth, Inflation, Financial and Macroeconomic Stability.

First Version: April 2025. This paper has greatly benefited in its various stages from comments received during the 14th BIS CCA Research Conference on "Macro-financial implications of climate change and environmental degradation", the BCRP research seminar, the BCRP Economists' Meeting in 2024, BCRP Economists' Meeting in 2023, discussion from Ilhyock Shim, conversations with Roberto Schaefer, and the excellent research assistance and helpful discussions with Joshelyn Binkley. We are grateful to Gabriel Chimoy, Gabriel Gálvez y Nicolas Ramirez for research assistance. The views expressed in this paper are those of the authors and should not be interpreted as reflecting the views of the Central Reserve Bank of Peru.

*Central Reserve Bank of Peru. E-mail: john.aguirre@bcrp.gob.pe
†Central Reserve Bank of Peru. E-mail: alan.ledesma@bcrp.gob.pe
‡Central Reserve Bank of Peru. E-mail: fernando.perez@bcrp.gob.pe
§Central Reserve Bank of Peru. E-mail: youel.rojas@bcrp.gob.pe

Contents

1 Introduction **3**

2 Literature Review **5**

3 Empirical Exploration **7**

3.1 ENSO and Local Variation 7

3.2 Data 9

3.3 Assessing the Impact of the ENSO on GDP and Inflation: LP Approach . 11

3.4 Robustness 19

3.5 Discussion 20

4 A Semi-Structural Model with ENSO Shocks **20**

4.1 The Model 20

4.2 Modeling the Effects of the ENSO on Central Bank's Credibility 24

4.3 Calibration 25

4.4 Results 27

5 Conclusion **33**

Bibliography **34**

A Bias in Local Projections **38**

B Robustness to Local Projections Estimation **40**

B.1 LP Monthly Estimation 40

B.2 LP Estimation with Sample Post COVID-19 Pandemics 41

B.3 LP Estimation for 3-digit CPI Components 42

C Robustness to Empirical Results **44**

C.1 Assessing the Impact of the ENSO on GDP and Inflation: a TVP-VAR-SV Approach 44

C.2 A Threshold BVAR Approach 45

D Semi-Structural Nonlinear Model **51**

D.1 The Model 51

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 decreased by 1.8%, primarily due to extreme weather events, and with disproportionate losses in low income regions (Rising, 2023). Global warming is expected to exacerbate this trend, leading to greater uncertainty about environmental conditions and future economic stability (Marticorena, 1999; Ribes et al., 2020). As a response to this evolving reality, central banks have increased their efforts to evaluate the wide-ranging impacts of climatic events on overall macroeconomic stability, as highlighted by Schnabel (2022). In this paper, we examine the economic impact of a large weather shock, El Niño Costero, in Peru.

El Niño Costero event, which is an important physical climate risk for several economies, including Peru, is a local version of El Niño-Southern Oscillation (ENSO).[1] In this document, we use "El Niño" or "ENSO" interchangeably to refer to El Niño Costero, which is the relevant climate phenomenon for our study. Cai and Santoso (2023) found that ENSO events occur more frequently due to climate change and lead to more intense weather events, such as droughts, floods, and heatwaves. Throughout history, El Niño-Southern Oscillation has significantly influenced weather patterns in Peru and had substantial economic impacts (Vargas, 2009). Major ENSO events in the 1982-1983 and 1997-1998 periods caused economic losses equivalent to 11.6% and 6.2% of annual GDP, respectively (Senamhi, 2014). Future projections by Callahan and Mankin (2023) estimate that, even with current national commitments to reduce emissions, the increase in frequency and intensity of ENSO events will cost the global economy \$84 trillion in this century.

We delve into the case of Peru, a country vulnerable to the effects of El Niño, to understand the wide range of effects of its shocks on inflation, inflation expectations, aggregate output, and sector-specific inflation and economic activity. From this evidence, we draw implications for monetary policy. In particular, this paper seeks to answer the following questions: What is the dynamic response of inflation and economic activity after a El Niño shock? What underlying forces drive the short- and medium-term responses of these macroeconomic variables? What are the implications of these types of shocks for the design of monetary policy?

First, we explore the significance of large weather shocks caused by ENSO in the Peruvian economy by using three methodologies: state-contingent Local Projections, as our main methodology, and a TVP-VAR model and a Threshold-BVAR model, as our robustness methodologies.[2] With respect to our main framework, Local Projections (LP) are not only relatively more robust to missspecification but also easy to estimate, via linear regression (Jordà and Taylor, 2024). With this tool in hand, our empirical analysis identifies key stylized facts about the nonlinear effects of large weather shocks, observed during El Niño events, on inflation and economic activity. Furthermore, this approach enables us to extend the analysis by examining how these shocks impact various sectoral components

[1] This irregular but recurrent phenomenon cause significant year-to-year variations in global climate conditions (Greenberg, 2023).

[2] For the estimation of dynamic effect of the El Niño on aggregate macroeconomic variables we use a non-linear specification of the original Local Projection (Jordà, 2005), by following the literature that studies the responses to monetary and fiscal policy shocks, allowing for variations across regimes determined by a state variable (among other see for example Tenreyro and Thwaites (2016); Auerbach and Gorodnichenko (2012)). 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.

underlying the broader macroeconomic aggregates.

Our measure of weather shocks is the ICEN index (Índice Costero El Niño), which captures both the occurrence and the intensity of El Niño Costero events. This index is produced by the Peruvian ENSO Center and is based on the three-month moving average of sea surface temperature anomalies in the 1+2 region of the Pacific Ocean, relative to the long-term mean (calculated over the 1981–2010 period). We focus on large El Niño Costero shocks: events with an intensity of Moderate or higher (ICEN higher than 1). Our identification relies on the exogeneity of the ICEN evolution. However, because the ICEN index exhibits serial correlation, it introduces bias into the coefficient of contemporaneous temperature. Accordingly, we refine our Local Projections (LP) specification by modifying the lag structure of the El Niño regime identifier, and incorporating an ICEN shock. We estimated the LP impulse responses of macroeconomic variables to an ICEN shock, calibrated to represent the typical characteristics—both in duration and intensity—of historically strong El Niño events.

In the first year following the onset of the El Niño shock, annual inflation rises sharply by nearly 4%. This rise in the CPI level proves persistent, with prices remaining elevated, even three years after the shock. This persistent effect on overall prices reflects the differential response of its two main components: within one year, the response of food and energy CPI dominate the total price dynamics, while its medium-term dynamics is driven by core CPI (non food and energy CPI). The response of inflation expectations to an ENSO shock emerges with a two-quarter lag, after which expectations begin to rise persistently. It is only after two years that these elevated inflation beliefs gradually subside, returning close to their pre-shock levels.

In response to the ENSO shock, the aggregate GDP declines by approximately 0.6% in the first quarter, a contraction largely driven by the primary sector, which falls by about 3.7% in the first quarter and nearly 6% over the following three quarters. While the initial GDP contraction appears modest, the negative effects deepen over time. By the second year after the shock, GDP reaches its lowest point, with output nearly 5% below its pre-shock level. This substantial decline is primarily driven by the delayed response of the non-primary sector. These empirical findings indicate that El Niño generates large and statistically significant effects on potential GDP, relative to the output gap. Fluctuations in the primary sectors primarily reflect supply-side shocks, which are closely tied to changes in potential output. In contrast, variations in non-primary sectors are influenced by a combination of demand and supply shocks. However, the highly persistent nature of El Niño's effects suggests that trend shocks—those affecting potential GDP—are the dominant force at play.

The empirical findings suggest that El Niño shocks exhibit characteristics similar to supply-side shocks, as they simultaneously generate upward pressure on inflation and reduce GDP. These effects are particularly persistent, affecting both the price level and aggregate output over an extended period. These features of the El Niño events pose challenges for monetary policy implementation.

Second, to assess the significance of El Niño for inflation and output stabilization we integrate the empirical findings into a semi-structural model, via impulse response matching. Our semi-structural model incorporates the asymmetry of the El Niño shock by including five nonlinear transmission channels. The first four are motivated by our empirical results and depend on the El Niño coastal index level (ICEN, for its acronym in Spanish), while the last one is driven by concerns that these events may become more frequent and intense in the future, which could impact the bank's ability to anchor public expectations.

When the ICEN index exceeds 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 i turn reduces demand. Furthermore, when El Niño shock intensifies and the ICEN index surpasses the level of two, two additional channels are activated: (iii) a potential GDP loss channel, due to extreme weather events like droughts and floods that disrupt production and damage the infrastructure, and (iv) an inflation expectation channel, where persistent inflation and production disruptions lead to heightened inflation expectations. The final channel our model accounts for is (v) the credibility channel. Frequent inflation deviations from its target, caused by El Niño, can undermine trust in monetary authorities and alter the way market participants form their 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.

In this nonlinear framework, the economic uncertainty and the costs of stabilizing the economy are closely linked to the frequency of El Niño events. The irregular and unpredictable nature of these climate shocks complicates the formulation of effective monetary policies. In the presence of an El Niño shock, conventional monetary policy strategies aimed at stabilizing headline inflation, core inflation, and inflation expectations tend to entail significant trade-offs, leading to a wider output gap and greater exchange rate appreciation. Nevertheless, 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. As a result, the effectiveness of these approaches must be assessed carefully, balancing the need to control inflation against the goal of sustaining economic growth.

Furthermore, for El Niño events that are more frequent and intense over time, deviations in inflation from its target undermine the credibility of monetary authorities, requiring additional monetary policy instruments or alternative measures. Repeated supply shocks lead to higher inflation fluctuations and reshape how economic agents form their expectations, which can potentially cause inflation expectations to become unanchored. Consequently, traditional monetary policy loses effectiveness, creating opportunities for alternative tools such as improved communication strategies or broader fiscal and structural policies. Therefore, carefully calibrating monetary policy is essential to reducing negative impacts on both inflation and real economic activity.

The reminder of this paper is organized 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 is matched with our empirical results. It is through the lens of this model that we are able to discuss monetary design once these shocks hit. Finally, Section 5 concludes.

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 that 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 time series techniques, 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, they are 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. Chirinos 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% reduction in the country's potential GDP.

Evaluating data of past ENSO in Peru, CEPAL (2014) concludes that El Niño and La Niña[3]. 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 for years.

This paper 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 to show that physical risks act like negative demand shocks while transition risks induce downward supply movements. In contrast, Pozo and Rojas (2024) observe that climate disasters data across a sample of

[3] ENSO has two phases that are characterized by above average sea surface temperatures in the eastern Pacific Ocean during El Niño and below average during La Niña.

developed and developing economies provide evidence that physical risks from climate-related events act as negative supply shocks: they 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., 2023a). 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.

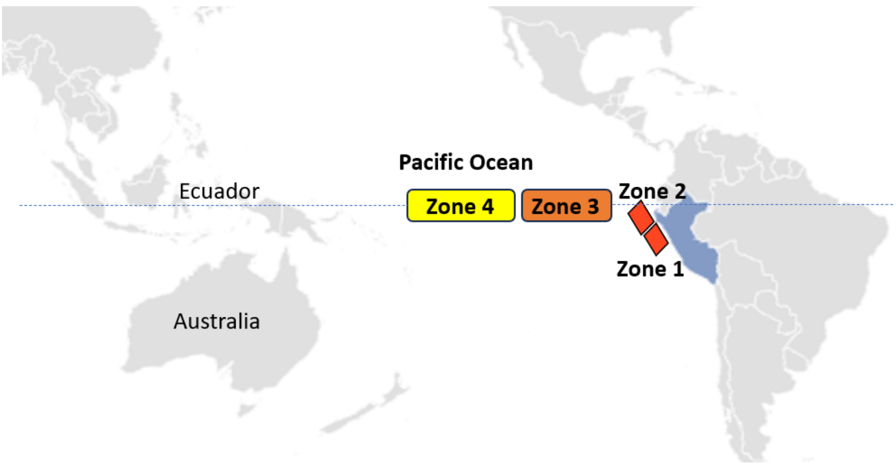
3 Empirical Exploration

This section presents our empirical strategy to characterize the dynamic effects of large El Niño shocks on the Peruvian economy, by estimating 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, the Local Projections specification is presented, which is our main methodology to estimate the impulse responses of macroeconomic and sectoral variables to these shocks. For robustness, we also present results from two other methodologies: a TVP-VAR, and a Threshold-BVAR.

3.1 ENSO and Local Variation

El Niño-Southern Oscillation (ENSO) is a large-scale periodic disruption of 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 has 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*

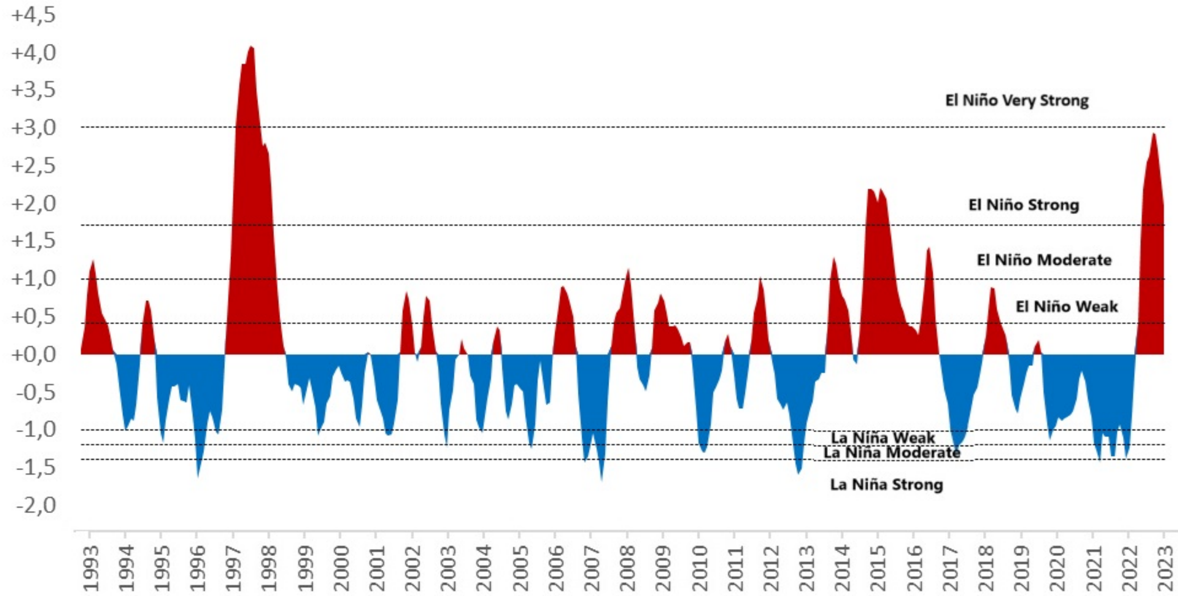


The Peruvian ENSO center, Estudio Nacional del Fenómeno del Niño (ENFEN), monitors the sea surface temperatures and report the ICEN index (Índice Costero El Niño), which determines the occurrence and magnitude of El Niño Costero. This index is derived from the Extended Reconstructed Sea Surface Temperature series (ERSST) reported monthly by The 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 the ICEN index and Table 1 presents the different categories for El Niño and La Niña according to their ICEN index values.

Table 1. *ICEN Categories*

		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 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).

3.2 Data

The empirical exploration relies on monthly economic databases from the Central Reserve Bank of Peru (BCRPData) for the 1994M1-2019M12, covering Peruvian economic variables: total GDP index, primary GDP index, non-primary GDP index, sector-specific production indices; consumer price index (CPI), food and energy CPI index, non food and energy CPI index, and a measure of inflation expectations twelve months ahead. Other variables are also selected as controls in our main specification: terms of trade, foreign exchange rate (PEN soles per US dollar), short-term domestic interest rates, total liquidity, oil prices, and copper prices. We also consider an extended sample until 2024M10 for robustness. We do not consider the extended sample until 2024M10 for main estimates since after 2019M12 other large shocks increased the volatility of the data and made the estimation process more difficult: Covid-19 pandemic and the post pandemics large global inflation.

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

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 that this El Niño reduced Global 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	Not Available.
3/1992-6/1992	4	Strong	Global GDP dropped by 2.5% in 1992 as a result of El Niño[c].
4/1993-6/1993	3	Moderate	Not Available
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 that this El Niño reduced Global 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	Not Available
5/2012	1	Moderate	Not Available
6/2014-7/2014	2	Moderate	The 2.3% Global 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	Not Available
2/2017-4/2017	3	Moderate	This El Niño contributed to a 0.8% drop in Global 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 Global 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) categorized from "Weak" to "Very Strong", reflecting the magnitude in which sea surface temperatures (SST) reach values above historical averages for El Niño or below historical averages for La Niña, as shown in Table 1. We focus on large climate El Niño shocks: events with an intensity of Moderate or higher (ICEN higher than 1). Between 1993 and 2023, there have been 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

A non-linear Jordà (2005) Local Projections (LP) methodology is used to estimate the dynamic equilibrium response of prices and GDP after an anomalous climate shock resulting in an El Niño state. This approach allows us to estimate impulse responses that vary across ICEN index temperature regimes. Therefore, for a given outcome of the log of variable y, we can derive state-dependent impulse responses to large El Niño shocks using the following LP non-linear specification:[4]

$$y_{t+h} - y_{t-1} = (1 - I_t)[\alpha_{0,h} + \beta_{0,h} x_t + B_{0,h} X_t] + I_t[\alpha_{1,h} + \beta_{1,h} x_t + C_{1,h} X_t] + e_{t+h}\,, \tag{3.1}$$

$$I_t = \mathcal{I}(x_t > 1)\,,$$

where $y_{t+h} - y_{t-1}$ is a long difference, $h = 1, \ldots, 36$, 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 and X_t is a vector containing a set of controls. Note that we specify the dependent variable not in levels but in long-differences to reduce any small sample bias (Piger and Stockwell, 2023; Jordà and Taylor, 2024).

The coefficients of interest in equation (3.1) are $\beta_{1,h}$ for all h. These are dynamic responses that indicate the cumulative change at horizon h of y (e.g., CPI or GDP in our case) in response to an anomalous climate shock as a result of El Niño. The vector X collects all the control variables considered. Common controls for prices and aggregate GDP as outcome variables include the following: one lag of the dependent variable, one lag of the controls: ICEN index, the oil price index growth, terms of trade, foreign exchange rate, short-term interest rate, total liquidity.[5] In our estimation, we include GDP as a control variable when analyzing prices, and conversely, we include prices as a control variable when analyzing GDP. When the dependent variable is a component of GDP or prices, the remaining components are also included as controls. Furthermore, for the sectors of GDP, the vector of controls also includes a dummy variable for the start of large mining projects and the price of copper to allow control for idiosyncratic dynamics.

The outcome variable y_{t+h} is a measure of CPI 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.

[4] This LP non-linear specification has been employed in the literature to estimate impulse responses to monetary and fiscal policy shocks, allowing for variations across regimes determined by a state variable. For example Tenreyro and Thwaites (2016); Angrist et al. (2018); Jordà et al. (2024) indicates that monetary policy impacts vary with the state of the economy. Auerbach and Gorodnichenko (2012); Jordà and Taylor (2016); Ramey and Zubairy (2018) show fiscal policy effects are economic cycle-dependent.

[5] Following Jordà and Taylor (2024) we selected the optimal lag for the LP using the optimal lag chosen by the Bayesian Information Criterion (BIC) criterion applied to a corresponding VAR model for the variables considered.

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 high persistence. In fact, the ICEN index follows a persistent dynamics, which is identified to be better captured by an ARMA(2,3) model, given by[6]

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

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 2024m10.

Because the ICEN index exhibits serial correlation, it introduces bias into the coefficient of contemporaneous temperature. Simply including lagged ICEN values is insufficient to address this issue. Therefore, we modify equation (3.1) y adjusting the lag structure of the indicator variable I, and incorporating an ICEN shock. This shock, represented by $\hat{\varepsilon}_t$, is the maximum likelihood residual obtained from equation (3.2). See Appendix A for a complete discussion on this problem derived from the persistence of x and the structure of the dummy variable I, along with the derivation of the solution. Consequently, we estimate the following specification:

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

However, when the dependent variables, y, is the 12-month ahead inflation expectations, we specify the model in levels of the form:

$$y_{t+h} = (1 - I_{t-1})[\alpha_{0,h} + \beta_{0,h}\hat{\varepsilon}_t + B_{0,h}X_t] + I_{t-1}[\alpha_{1,h} + \beta_{1,h}\hat{\varepsilon}_t + C_{1,h}X_t] + e_{t+h} \tag{3.4}$$

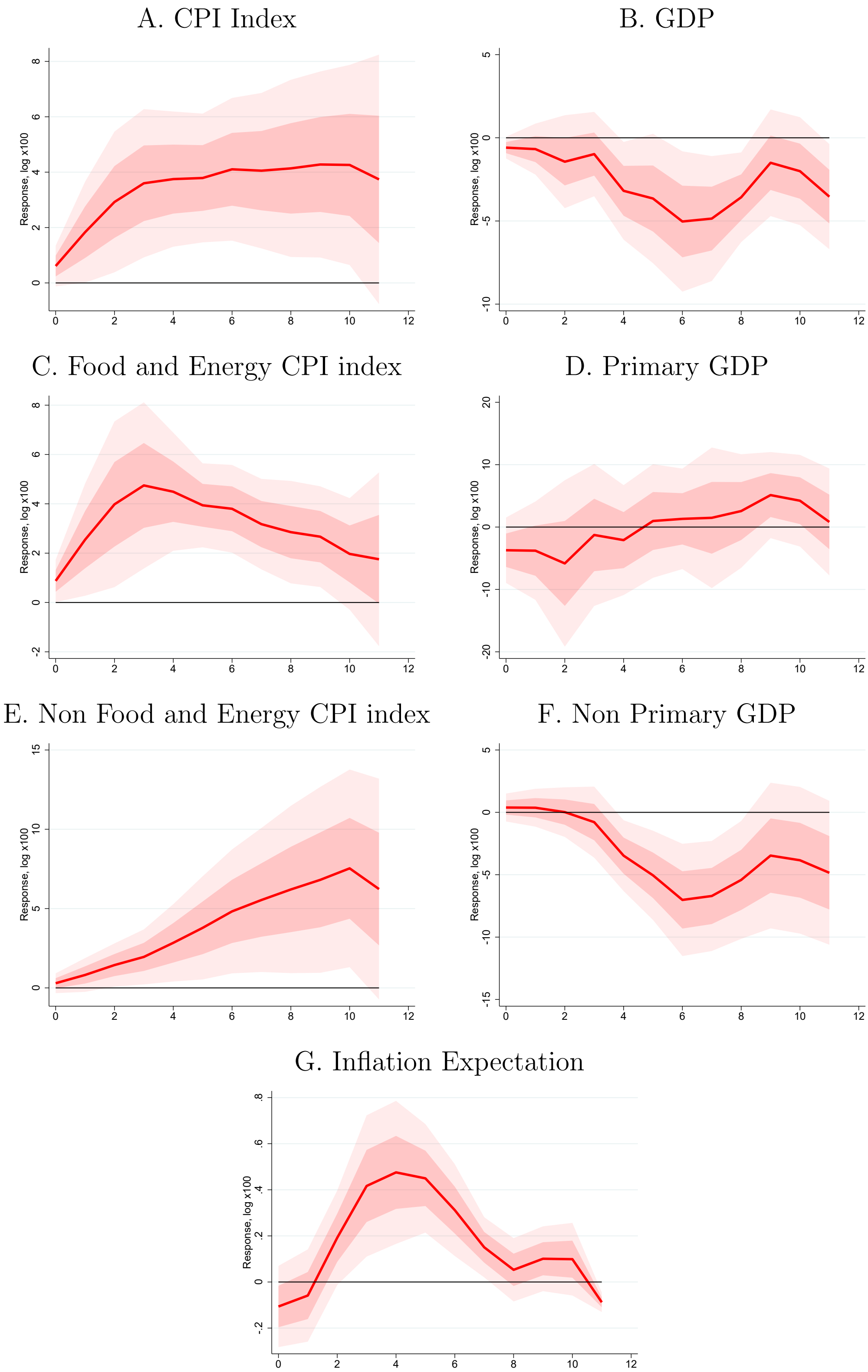
Table 3. *ICEN as an ARMA(2,3) process*

	Coef.	Std. Err.	z	$P > \|z\|$	[95% Conf. interval]	
ρ_0	-0.233	0.109	-2.130	0.033	-0.446	-0.019
ρ_1	1.712	0.077	22.37	0.000	1.562	1.862
ρ_2	-0.755	0.068	-11.100	0.000	-0.888	-0.621
ϕ_1	0.301	0.091	3.310	0.001	0.123	0.479
ϕ_2	0.270	0.090	2.990	0.003	0.093	0.447
ϕ_3	-0.659	0.089	-7.380	0.000	-0.833	-0.484
σ_ε^2	0.151	0.003	49.430	0.000	0.145	0.157
Sample:			Feb-1950 to Apr-2024 (891 observations)			

Note: Maximum likelihood estimates.

[6] Optimal ARMA model chosen using the Bayesian Information Criterion (BIC) criterion.

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



Note: LP impulses to an ICEN shock, provided that the initial ICEN index value is greater than 1. Strong El Niño event (see the main text). Estimates from monthly LP estimates. y-axis in Panels A to F the outcome is the cumulative change of 100 times the log of the variable. The variable is the 3-month moving average of the price or GDP index. Only the last month of each quarter is depicted. For the y-axis in Panel G, the outcome is the change in inflation expectations. The quarterly response of inflation expectations is as a 3-month moving average of the monthly impulse responses. x-axis: quarters after the shock. Red shaded areas are one and two standard deviation pointwise confidence bands using heteroscedasticity robust standard errors. Sample 1994m01-2019m12.

Results

Figure 3 presents the quarterly LP impulse responses of macroeconomic variables to an ICEN shock, calibrated to represent a strong El Niño event. Specifically, we use equation (3.2) to generate a shock to the ICEN index that simulates an El Niño episode lasting nine months, with an average magnitude of 1.7. This calibration closely reflects the typical characteristics—both in duration and intensity—of historically strong El Niño events.[7]

Each panel in Figure 3 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 quarters after the shock. The red solid lines represent the mean response, while red shaded areas are one and two standard deviation pointwise confidence bands using heteroscedasticity robust standard errors.

It is important to note that later in Section 4 we align this LP impulse responses with those from a semi-structural quarterly model. Consequently, our monthly estimation were adjusted accordingly to obtain quarterly estimates. Specifically, we first apply a 3-month moving average to the indices of prices and GDP, take the logarithms of these variables, and then estimate our LP specification as outlined in equation (3.3). This transformation ensures that the impulse response for the last month of each quarter approximately matches the quarterly response to the shock. Thus, we plot the last month estimation of each quarter. For inflation expectations, which are already expressed as a percentage rate, we directly estimate equation (3.4) using our monthly data and derive the quarterly response as a 3-month moving average of the monthly impulse responses. Appendix B.1 shows that the monthly LP without any 3-moving average transformation to the data of prices and GDP give similar impulse responses, but with a much more noisier looking responses and potentially less precise.

Effects of el Niño on prices

Panel A in Figure 3 shows that an El Niño shock triggers a sharp increase in prices over one year. One year later, prices are almost 4% higher than at the onset of the shock, equating to an annual inflation rate of nearly 4%. These effects are statistically significant and persistent. The sharp inflationary effects begin to ease after the first year, with subsequent increases slowing down until the cumulative price impact is just above 4% two years later. Three years after the shock, prices remain elevated and close to 4%. This persistent effect on overall prices reflects the differential response of its two main components: the food and energy CPI, and the core CPI (which excludes food and energy). In the short term—within the first year—the impact of food and energy prices has the greatest influence on overall price dynamics. However, in the medium term, it is the core CPI that drives the evolution of prices.

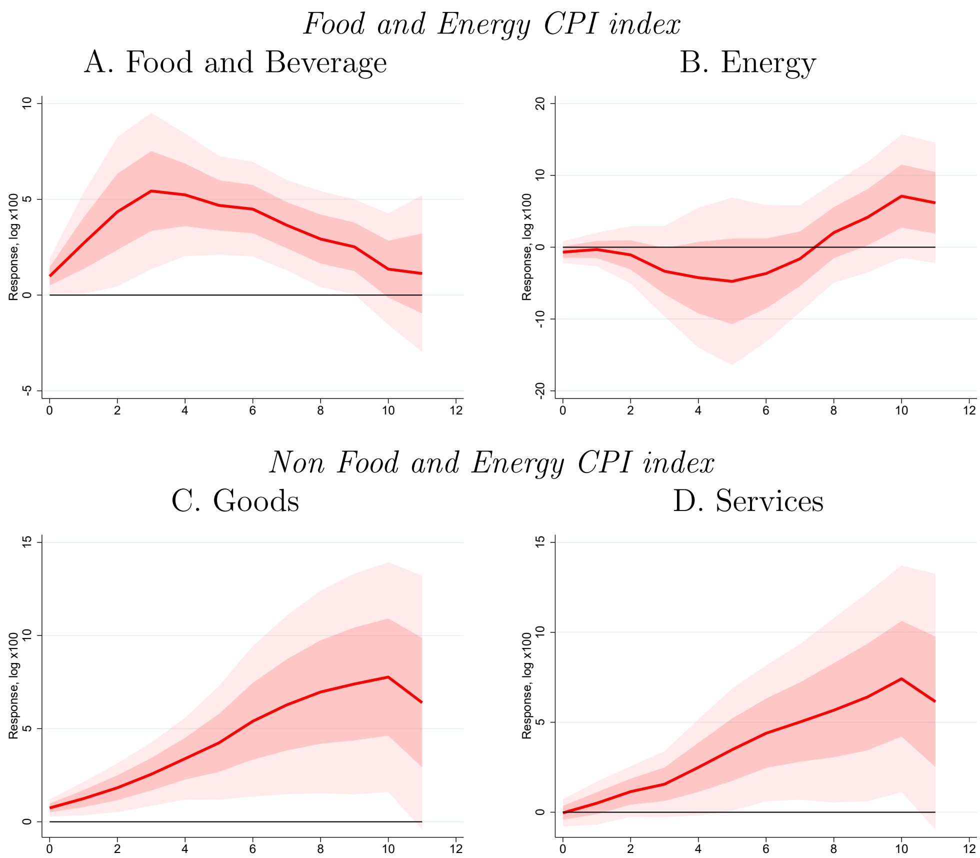
Panel C provides evidence that in the first year, the majority of overall inflation variation is due to El Niño's substantial impact on food and energy inflation. The total inflation response mirrors that of the food and energy inflation, which, four quarters after the

[7] Historical data on the ICEN index from 1951 to 2004 indicate the occurrence of 19 El Niño events with an ICEN value exceeding 1, corresponding to at least moderate intensity. On average, these events lasted 5.3 months and had a mean ICEN magnitude of 1.5. Among them, seven events reached a classification above strong, exhibiting an average duration of 9.86 months and an average ICEN magnitude of 2.1.

shock, reaches around 4.5%. Subsequently, food and energy prices begin to decline steadily, with the price index being about 1.5% lower, relative to the peak impact, two years later, and the effects of the shock nearly dissipate by the third year. Panel E indicates that in the quarters following the first year, the total CPI index is significantly influenced by its non-food and energy price components. After two years, non-food and energy prices are around 5.5% higher than at the shock's onset and continue to rise, showing only a slight indication of reversion 11 quarters later.

To understand in more detail the effects of El Niño shocks on prices, we computed the impulse responses of the 2-digit and 3-digit components of the CPI.

Figure 4. *LP: Quarterly Effects of El Niño on 2-digit components of CPI*



Note: LP impulses to an ICEN shock, provided the initial ICEN index value is greater than 1. Strong El Niño event (see the main text). Estimates based on monthly data. y-axis is the cumulative change of 100 times the log of the price index. The variable is the 3-month moving average of the price index, with only the last month of each quarter displayed. Red shaded areas are one and two standard deviation pointwise confidence bands using heteroscedasticity robust standard errors. Sample 1994m01–2019m12.

Panel A in Figure 4 indicates that the short-term inflation response is primarily driven by the direct effects of El Niño on the 2-digit components of food and beverages. Specifically, Figure 11 in Appendix B.3 further indicates that the 3-digit food and beverages at home component is mainly responsible for the short-run response of the total CPI. Conversely, the 3-digit food away from home CPI component exhibits a lagged response. Panel B in Figure 4 depicts the response of the CPI Energy index, which is almost null and even negative during the first year following the shock.

Panels C and D in Figure 4 illustrate that, in the medium term, overall inflation reflects the broad and consistent rise across all 2-digit components of goods and services within the core CPI. However, the goods CPI reacts more promptly to the El Niño shock compared to the services CPI, which shows a more delayed response. Figure 11 in Appendix B.3 further indicates that the 3-digit price components of furnishings, supplies, transportation, and recreation commodities are the most responsive, followed by the prices of household appliances. For the services CPI, most components show a minimal response during the first year. However, substantial and steady increases are observed during the second years, with prices remaining elevated thereafter. Later, there are weak and varied signals of reversion after 10 quarters following the onset of the shock. An exception is transportation prices, which only begin to show a sharp and significant increase seven months after the shock occurs.

Effects of El Niño on output

Panel B of Figure 3 displays the GDP response following the ENSO shock. Aggregate GDP declines by approximately 0.6% in the first quarter, a drop that is statistically significant. As illustrated in Panel D, this contraction is largely driven by the primary sector, which falls by about 3.7% in the first quarter and nearly 6% over the first three quarters. These sector-specific effects are not statistically significant at the 95% confidence level. We later demonstrate that this is due to the heterogeneous responses within the primary sector.

While the initial GDP contraction appears modest, the negative effects deepen over time. By the second year after the shock, GDP reaches its lowest point, with output nearly 5% below its pre-shock level. As shown in Panel F, this substantial decline is primarily driven by the delayed response of the non-primary sector.

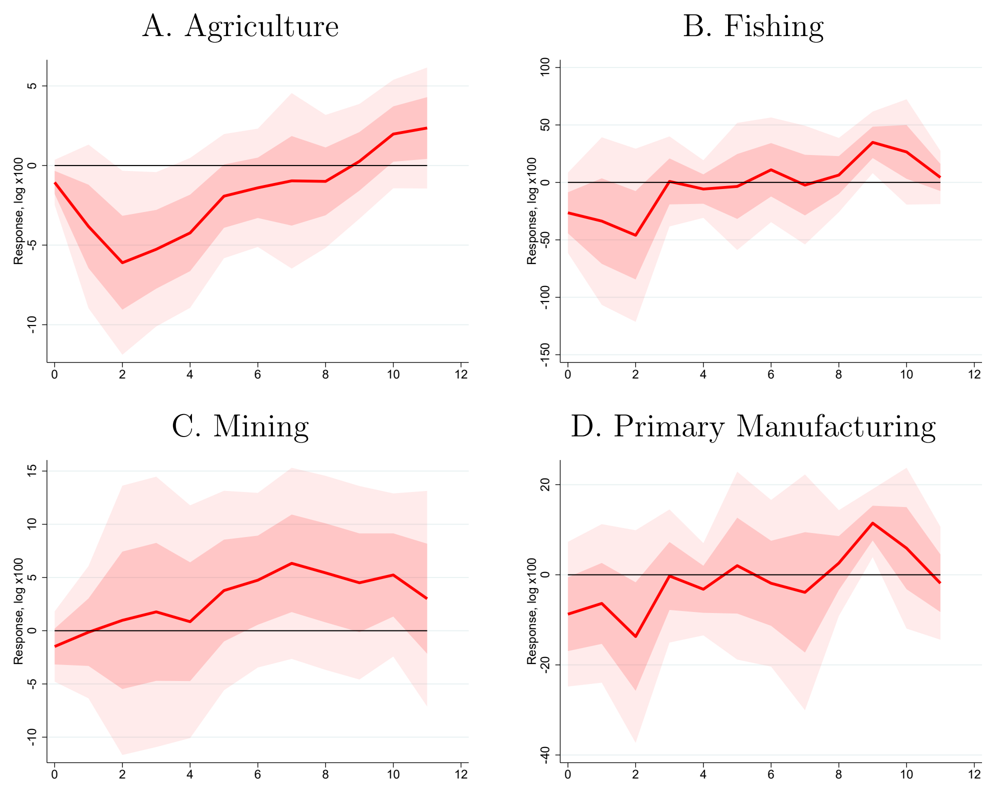
Overall, GDP exhibits a persistent downward trajectory. This sustained impact suggests that the El Niño shock generates long-lasting disruptions, particularly in non-primary sectors. One plausible explanation is the propagation of damages caused by associated natural disasters, such as landslides and mudslides, which can destroy critical capital infrastructure—including buildings, roads, and machinery—thereby impairing the productive capacity of the economy. The results show that these effects are not merely transitory but have enduring consequences for overall economic performance.

To better understand the heterogeneous effects of El Niño, we estimate impulse responses by economic sector, as shown in Figures 5 and 6, which report results for both primary and non-primary GDP components. Panels A, B, and D of Figure 5 highlight the primary sectors most affected by El Niño shocks are fishing, agriculture, and primary manufacturing. These sectors react immediately to the shock, with fishing experiencing the most pronounced contraction, declining by approximately 27%. Primary manufacturing follows with a reduction of around 8%, while agricultural output initially drops by about 0.9%.

The maximum negative impact on these sectors is observed in the third quarter following the shock. Fishing and primary manufacturing show relatively rapid recoveries thereafter, although the responses are not statistically significant at the 95% confidence level. In contrast, the agricultural sector exhibits a more gradual and persistent downturn. Its output reaches a trough three quarters after the shock, with a cumulative decline of roughly 5.5%. Compared to other primary sectors, agriculture demonstrates a notably slower recovery, with negative effects persisting for over a year. This pattern suggests a prolonged period of contraction in the agricultural sector following El Niño events.

In contrast, the mining sector (Panel C) shows negligible effects to an ENSO shock, with any effects that are not statistically significant.

Figure 5. *LP: Effects of El Niño on Primary GDP sectors*



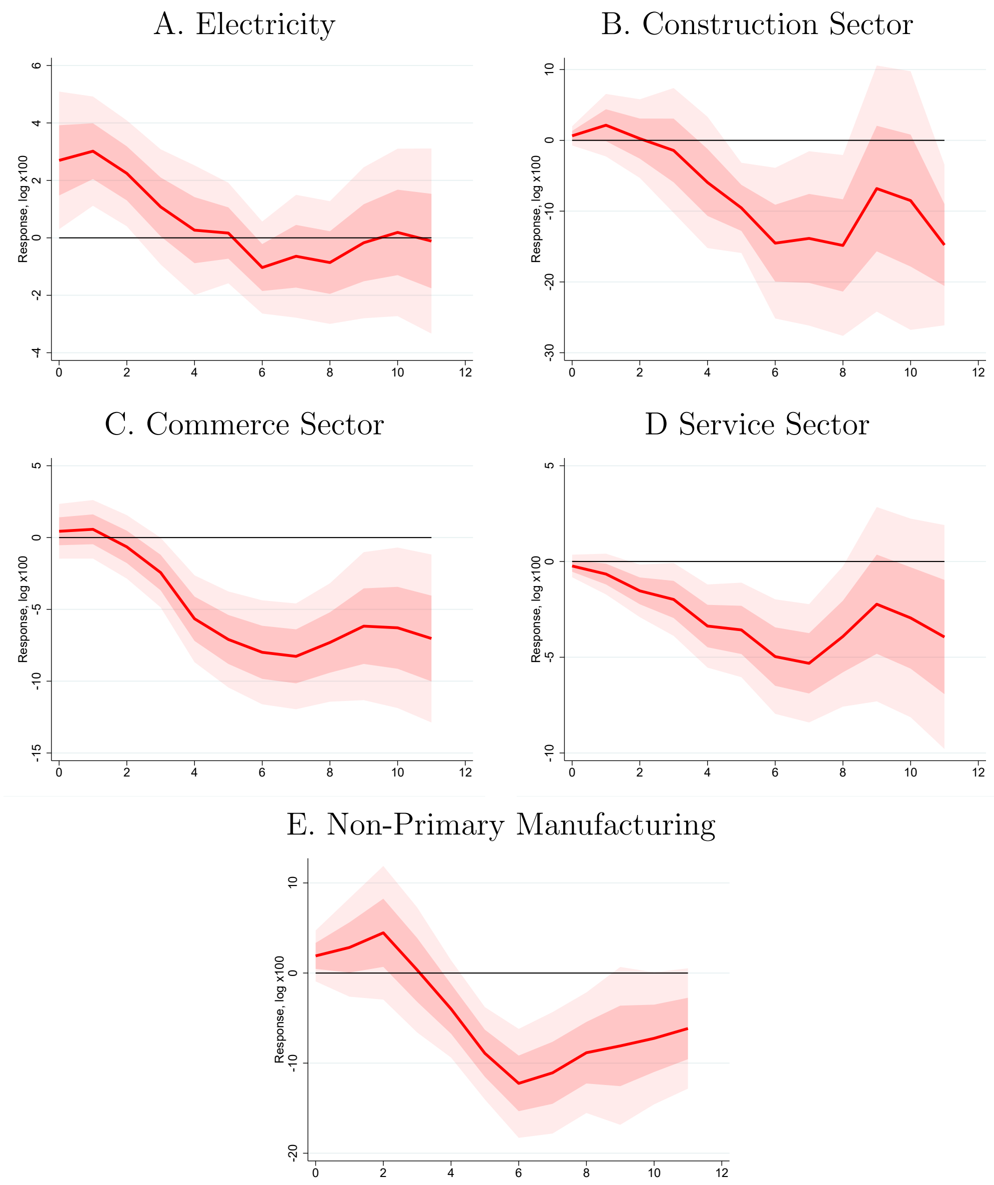
Note: LP impulses to an ICEN shock, provided the initial ICEN index value is greater than 1. Strong El Niño event (see the main text). Estimates from monthly LP estimates. y-axis: the outcome is the cumulative change of 100 times the log of the variable. The variable is the 3-month moving average of the GDP sector index. Only the last month of each quarter is depicted. x-axis: quarters after the shock. Red shaded areas are one and two standard deviation pointwise confidence bands using heteroscedasticity robust standard errors. Sample 1994m01–2019m12.

Figure 6 presents the impulse responses of non-primary sectors to an El Niño shock. In contrast to the immediate and sharp responses observed in primary sectors, the non-primary sectors display more delayed and moderate effects in the first year of the onset of the shock. An exception is the electricity sector, which exhibits a small but positive initial response. But, the negative impacts, when they do emerge, appear with varying lags: one quarter in the services sector, three quarters in commerce, and five quarters in construction and non primary manufacturing.

Once these effects materialize, however, they tend to persist longer than those in the primary sectors. Among non-primary sectors, commerce experiences the most prolonged and statistically significant downturn. The non primary manufacturing and the services sector begins to recover after approximately seven quarters, while construction shows early signs of improvement after eight quarters. These recoveries are weak and uneven across non-primary sectors.

In summary, the impulse responses of GDP across all economic sectors indicate a marked difference between primary and non-primary sectors. 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 immediate impact on potential GDP, as we have already deduced from the impulse responses of aggregate GDP. Additionally, the persistent negative responses in the non primary GDP sectors indicate that the more significant effects on potential GDP also materialize with some lag.

Figure 6. *LP: Effects of El Niño on Non Primary GDP sectors*



Note: LP impulses to an ICEN shock, provided the initial ICEN index value is greater than 1. Strong El Niño event (see the main text). Estimates from monthly LP estimates. y-axis: the outcome is the cumulative change of 100 times the log of the variable. The variable is the 3-month moving average of the GDP sector index. Only the last month of each quarter is depicted. x-axis: quarters after the shock. Red shaded areas are one and two standard deviation pointwise confidence bands using heteroscedasticity robust standard errors. Sample 1994m01–2019m12.

Effects of El Niño on inflation expectations

Finally, Panel G of Figure 3 shows the response of inflation expectations to an ENSO shock. The initial effect is slightly negative but not statistically significant. By the third quarter, however, expectations begin to rise, reaching a peak of approximately 45 basis points one year after the shock. Although the effects gradually decline thereafter, inflation expectations remain elevated relative to their pre-shock level for an additional four quarters. Two years after the shock, the higher inflation beliefs dissipate, and return close to their initial level.

3.4 Robustness

Our sample covers the period until 2019 and excludes a very strong El Niño event in 2023. This is due to heightened data volatility after 2019, driven by significant global disruptions such as the COVID-19 pandemic and the spike in global inflation. We consider robustness to include the post-COVID-19 data.

Our previous analysis of the effects of El Niño on the Peruvian economy, using LP 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 C.1 describes the specification of the model.

We also explore the robustness of our LP 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 C.2 offers a complete description of the model.

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

Results

Our main findings remain robust when extending the sample to include the post-COVID-19 period, as illustrated in Figure 10 in Appendix B.2. The local projection impulse responses are largely unchanged, with the notable exception of inflation expectations, which exhibit a more immediate increase following the onset of the shock, with subsequent responses that are stronger and more persistent.

The robustness results from the TVPBVAR and Threshold BVAR models 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 13 in Appendix C 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 14 in Appendix C 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 is presented in Appendix C.

3.5 Discussion

The empirical findings from the previous empirical exploration suggest that the economic impacts of El Niño shocks resemble those of supply-side shocks, by simultaneously exerting inflationary pressures and contracting GDP. These effects are notably persistent, in both prices and aggregate output. In the short run, the inflationary response is primarily driven by food prices, which tend to normalize within a year. However, over the medium term, core components of the Consumer Price Index begin to dominate the inflation dynamics. Notably, both core inflation and inflation expectations exhibit persistence, remaining elevated for more than a year.

This distinctive macroeconomic pattern carries important implications for monetary policy. El Niño shocks disrupt the typical relationship between inflation and economic activity, much like other supply-side disturbances. The central bank's policy response is limited or even absent if the shock is perceived as temporary and does not de-anchor inflation expectations. However, if inflation expectations begin to drift, the central bank faces a more complex scenario, and need to respond, given its constitutional mandate to maintain monetary stability. We further explore these challenges in the next section using a semi-structural model framework.

Our results also show heterogeneous effects across sectors. The impact on primary sectors is more immediate and larger, but the effects on non-primary sectors while smaller in the first year, are much more larger and persistent later on. The contractionary effects of El Niño in the short run are driven by sharp declines in primary sectors, mainly agriculture, fishing and primary manufacturing, while in the medium run, they are sustained by the persistent negative impacts on almost all non-primary GDP sectors. Overall, the very persistent negative effects points to the dominance of negative trend shocks associated with lower potential GDP.

In the following section we further discuss this large aggregate consequences of El Niño shocks for monetary policy using a semi-structural model calibrated for the Peruvian economy.

4 A Semi-Structural Model with ENSO Shocks

In this section, our goal is to evaluate how climate distress, within a macro framework that consider 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. Given that El Niño affects the economy through complex and non-linear channels, this modeling framework is particularly appropriate. Its flexibility allows for the straightforward incorporation of ad hoc components, making it well-suited to capture the multifaceted nature of these shocks.

In particular, we incorporate into the semi-structural model of Aguirre et al. (2022) five non-linear transmission channels through which El Niño affects the economy. When the ICEN index surpasses one, it activates two channels: (i) an inflationary surge driven by increased food and energy prices, and (ii) a demand reduction as higher food and energy prices diminish consumer disposable income, leading to decreased spending on other goods. As the El Niño shock intensifies, pushing the ICEN index above 1.7, two additional channels emerge: (iii) a potential GDP loss due to El Niño's extreme weather, which harms capital, reduces the labor factor and destroyed infrastructure, and (iv) an inflation expectations channel, where prolonged high inflation and production disruptions cause households to anticipate further price increases.

The final channel for which our model accounts is (v) the credibility channel. Frequent deviations of inflation from its target, caused by El Niño, can undermine trust in monetary authorities and alter the way market participants form their inflation expectations.

Those channels are consistent with the empirical results and depend upon the ICEN index: As illustrated in the impulse response function of GDP in Figure 3, the El Niño shock results in a permanent reduction in the GDP level. To capture this, we posit its effects on both potential GDP and the output gap. Primarily, we define El Niño as an extreme supply shock, leading to heightened levels and persistence of food and energy inflation, coupled with a demand contraction. Furthermore, in the case of a severe El Niño event, additional channels become active. These events induce a decrease in potential interannual GDP growth due to capital destruction and losses of lives. The output gap is influenced by a counteracting effect: demand declines, but at a slower rate than potential output, resulting in a temporary positive output gap. Finally, inflation expectations are affected solely during severe El Niño episodes, with (de-)anchoring consistent with observed increases in the persistence and level of inflation expectations following extreme supply shocks, as noted in BCRP (2017).

In the rest of the section, we focus on presenting how El Niño events activate the first four non-linear mechanisms within the semi-structural model, and defer a complete description of the model to the AppendixD.1. The credibility channel is explained in the next section.

The ENSO shocks and its transmission channels

We consider that ENSO shocks are governed by an exogenous stochastic process, which is also persistent. It is introduced in our quarterly model as an ARMA(3,4) process.[8]

$$ICEN_t = \alpha_0 + \sum_{j=1}^{3} \alpha_j ICEN_{t-j} + \varepsilon_t + \sum_{j=1}^{4} \beta_j \varepsilon_{t-j} \text{ with } \varepsilon_t \sim \mathcal{N}(0, \sigma_\varepsilon^2) \tag{4.1}$$

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 has an impact on output gap and inflation of food and energy when the ICEN index is bigger or equal than than 1. The model identifies another non-linearity associated with El Niño: when the ENSO index reaches or exceeds 1.7, it is considered sufficiently strong to disrupt production (by impacting production factors) and to cause de-anchoring of inflation expectations.

[8] In the empirical analysis presented in Section 3.3, we fit an ARMA(2,3) model to the monthly ICEN index. However, for the quarterly ICEN index—calculated as the average of the monthly indices within each quarter—a better fit is achieved with an ARMA(3,4) model. This is the best ARIMA(p,d,q) model for the ICEN in quarterly frequency following the BIC criterion.

Table 4. *Nonlinear effects of ENSO*

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

<u>*The effect of the ENSO on GDP*</u>

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

$$\Delta Y_t = y_t - y_{t-4} + \Delta Y_t^p \tag{4.2}$$

where ΔY_t is interannual GDP growth, y_t is the gap in production, and ΔY_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 presence of a extreme supply shock like a strong El Niño event, destruction of capital goods and lives occur, leading to a reduction of the level of product that can be sustained in the long term. Our specification for potential output, follows:

$$\begin{aligned}\Delta Y_t^p =&(1-\lambda^p)\Delta Y + \lambda^p \Delta Y_{t-1}^p + \Omega^{f/p}\left[I_{(ICEN_t>1.7)}ICEN_t + I_{(ICEN_{t-1}>1.7)}ICEN_{t-1}\right.\\ &\left.+I_{(ICEN_{t-2}>1.7)}ICEN_{t-2} + I_{(ICEN_{t-3}>1.7)}ICEN_{t-3} - I_{(ICEN_{t-4}>1.7)}ICEN_{t-4}\right] + \epsilon_t^p\end{aligned} \tag{4.3}$$

where ΔY 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. This specification of the El Niño effect on the potential growth rate follows the idea of a delayed impact over time. When the FEN is strong, it affects crop areas, water resources, and other productive factors in such a way that its impacts will materialize months or even quarters after the initial event.

In modeling the output gap, we account for two distinct effects. First, when an El Niño event begins to materialize — identified by $ICEN_t > 1$ — a delayed negative impact emerges. This threshold signals the onset of a negative wealth effect, as rising prices and declining economic activity reduce aggregate demand. Given that these effects unfold gradually, they are modeled with a one-quarter lag. Second, when the intensity of the shock increases — specifically when $ICEN_t > 1.7$ — potential output contracts more rapidly than demand, generating a temporary positive output gap. These effects are modeled as contemporaneous. The dynamic of output gap, y_t, is determined therefore by:

$$\begin{aligned}y_t =&a_y y_{t-1} + a_y^e\left(y_{t-1} + \Delta y_{t+1}^e\right) + a_\phi \phi_{t-1} + a_q q_t + a_g g_t + a_\tau \tau_t\\ &+ a_{y^*} y_t^* + \Omega^{f/y} I_{(ICEN_{t-1}>1)} ICEN_{t-1} + \Omega_y^{f/p} I_{(ICEN_{t}>1.7)} ICEN_t + \epsilon_t^y\end{aligned} \tag{4.4}$$

where Δy_t^e is economic agents' expectations regarding the output gap, which do not necessarily correspond with rational expectations, ϕ_t is a monetary condition index, q_t is the real exchange rate gap, g_t is the fiscal impulse, τ_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 ϵ_t^y is the aggregate demand shock. Analogously, $\Omega^{f/y} ICEN_t$ captures the reduction that El Niño causes on output gap after a quarter when $ICEN_t$ is bigger than one and $\Omega_y^{f/p} ICEN_t$ is the increase in the output gap when $ICEN_t$ is bigger than 1.7.

The specification of El on potential GDP and output intent to capture our empirical results. Our empirical results in Section 3.3 indicates that El Niño produces large significant effects on potential GDP relative to the output gap. El Niño has highly persistent effects on overall GDP. These effects are primarily driven in the short-run by the strong responses of its primary components, namely agriculture and fishing, and in the medium-run, by large and persistent responses of the non-primary GDP sectors. On one side, the fluctuations in the primary sectors mainly reflect supply shocks, which are directly associated with changes in potential GDP. On the other hand, movements in the non-primary sectors tend to reflect both demand and supply shocks. But, the very persistent effects of El Niño suggest the predominance of trend shocks that are linked to potential GDP changes. Therefore, we capture that in the semi-structural by making the effect on the output gap as a fraction of the effect on potential GDP.

The effect of the ENSO on inflation

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

$$\pi_t = c_{sae}\pi_t^{sae} + (1 - c_{sae})\pi_t^{ae} \tag{4.5}$$

Food and energy inflation is modeled using the next equation:

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

This equation describes the law of motion of food and energy inflation when El Niño occurs ($ICEN_t > 1$). It accounts for i) a direct shift ($\Omega^{f/ae}$), and ii) an increase in persistence ($\lambda^{f/ae}$) due to changes in the ICEN index.

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 rate is not directly affected by El Niño shock, but only indirectly via inflation expectations.

$$\pi_t^{sae} = b_m \Pi_t^m + (1 - b_m) \left[b_{sae} \pi_{t-1}^{sae} + (1 - b_{sae}) \Pi_t^e \right] + b_y y_{t-1} + \epsilon_t^{sae} \tag{4.7}$$

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 trend (excluding food and energy) four quarters in the future, Π_{t-1} is the inflation trend of the previous quartes, which is the average of previous four quarters, and $\epsilon_t^{\Pi^e}$ is the inflation expectations shock:

$$\begin{aligned} \Pi_t^e =& \lambda_{\Pi^e} \Pi_{t-1}^e + (1 - \lambda_{\Pi^e}) \left[c_{\pi^e} C_{t-1} E_t \Pi_{t+4}^{sae} + (1 - c_{\pi^e}) \Pi_{t-1} \right] + \dots \\ & \dots + (1 - C_{t-1}) \left[\Pi_{t-1} - Meta \right] + \Omega^{f/exp} I_{(ICEN_{t-3} > 1.7)} ICEN_{t-3} + \epsilon_t^{\Pi^e} \end{aligned} \tag{4.8}$$

The direct transmission channel of El Niño shocks to inflation expectations is captured by term $\Omega^{f/exp}ICEN_{t-3}$. The ENSO shock only has an effect on inflation expectations when it becomes deanchored, and we consider that it will only happen when the economy is hit by a strongly high weather shock, i.e., when $ICEN_t > 1.7$ and effects occurs three quarters later, as supported by our empirical results. C_{t-1} represents the credibility stock of the monetary authority, ranging between 0 (no credibility) and 1 (maximum credibility). When the credibility stock variable is less than 1 it weakens the prospective component of the inflation expectation and generates an inflation bias ($[1 - C_{t-1}]\,[\Pi_{t-1} - Meta]$), which increases inflation expectations in proportion to the deviation of the inflation trend of the previous quarter's from the inflation target. The dynamics of the credibility stock are explained in the next section.

4.2 Modeling the Effects of the ENSO on Central Bank's Credibility

Market participants form their inflation expectations based on the confidence they have in the monetary authorities. Often, deviations of inflation from its target can alter the trust the market has in these authorities, subsequently changing the way inflation expectations are generated.

From figure 3, we see that a strong El Niño episode significantly impacts inflation expectations for over seven quarters.

This issue holds importance for policymakers, as the effectiveness of monetary policy, particularly in achieving price stability, is contingent upon well-anchored inflation expectations. Consequently, we integrate this credibility channel into our analysis and assess its impact through simulations. Credibility is introduced through the stock variable C_t, following Benes et al. (2017), which ranges from 0 (absence of credibility) to 1 (full credibility) with law of motion:

$$C_t = \eta_1 C_{t-1} + (1 - \eta_1)s_t \tag{4.9}$$

where η_1 is the parameter that governs the persistence of the credibility balance, and s_t represents the credibility revision signal. This signal, constrained between 0 and 1, dynamically adjusts the credibility balance. The credibility revision signal is derived from an expectation formation mechanism that allows agents to switch between:

1. **Expectations of High inflation (H):** a pessimistic expectation formation process, which assigns weight to past realized inflation and a **high inflation value**.
2. **Expectations of Low inflation (L):** an anchoring expectation formation process, which is anchored to long-term inflation and allocates weight to past inflation and the **monetary authority's target**.

An increase in the credibility revision signal s_t indicates a greater reliance on the anchoring component in expectation formation. This signal is determined by the mean squared prediction errors of the aforementioned expectation formation models, exhibiting the following dynamics:

$$s_t = 1 - \eta_2 \frac{(\epsilon_t^L)^2}{(\epsilon_t^H)^2 + (\epsilon_t^L)^2} \tag{4.10}$$

$$\epsilon_t^H = \Pi_t - [\rho_H \Pi_{t-1} + (1 - \rho_H)\pi_H] \tag{4.11}$$

$$\epsilon_t^L = \Pi_t - [\rho_L \Pi_{t-1} + (1 - \rho_L)\bar{\pi}] \tag{4.12}$$

where η_2 is the coefficient that indirectly sets a minimum threshold for the central bank's credibility level, ϵ_t^L is the law of motion for the anchoring model, and ϵ_t^H is the law of motion for the pessimistic model. The anchoring model is a low-inflation regime where agents believe that inflation will converge to the announced target ($\bar{\pi}$). The pessimistic model, on the other hand, is a high-inflation regime where agents believe that the central bank can only achieve a high level of inflation above the target ($\pi_H > \bar{\pi}$).

Additionally, the following boundary conditions are defined:

- **High credibility state:** inflation is less than the one predicted by the anchoring model.

$$s_t = 1 \quad \text{if} \quad \epsilon_t^L < 0 \tag{4.13}$$

- **Low credibility state:** inflation is more than the one predicted by the pessimistic model.

$$s_t = 0 \quad \text{if} \quad \epsilon_t^H > 0 \tag{4.14}$$

Thus, the credibility of the central bank can be established based on the parameter η_2, which represents the weight agents place on the credibility signal and is inversely related to current inflation. Consequently, a more credible central bank diminishes the influence of current inflation on household expectations relative to the inflation target.

4.3 Calibration

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

The first group of model coefficients is estimated in Aguirre et al. (2022); hence, they are calibrated at their estimated posterior means. To incorporate the direct impact of climate change shocks on macroeconomic variables, we estimate the relevant coefficients using impulse response function matching estimators. Specifically, we align the impulse responses generated by our extended semi-structural model with those obtained from our LP estimation.

Figure 7 presents the results of the impulse response functions matching for CPI inflation, food and energy inflation, inflation expectations, and GDP growth. In the figure, blue lines with markers represent point estimates, while shaded areas indicate the corresponding 95% confidence intervals. Solid red lines depict the IRFs generated by our semi-structural model. To align the model with the four empirical IRFs, we estimate four key parameters:

(1) the sensitivity of potential growth to the ENSO shock, denoted as $\Omega^{f/p}$; (2) the sensitivity of food and energy inflation to the ENSO shock, denoted as $\Omega^{f/ae}$; (3) the increase in the persistence of food and energy inflation, denoted as $\lambda^{f/ae}$; and (4) the sensitivity of inflation expectations to the ENSO shock, denoted as $\Omega^{f/exp}$; and (5) the parameters that represent the sensitivity of the output gap to the ENSO shock ($\Omega^{f/y}, \Omega_y^{f/p}$) when is strong($ICEN > 1$) and severe($ICEN > 1.7$) are calibrated as a fraction of $\Omega^{f/p}$. We have four IRFs and five parameters to calibrate. The last parameter, which assesses the impact of ENSO on the output gap, is set as a fraction of its effect on potential output. We estimate these effects to be in a proportion of 1 to 10.[9] These parameters are presented in Table 5.

Table 6 presents the parameter estimates of the ARMA(3,4) model, which is the best empirical fit for the exogenous univariate model representing the ICEN index.

Finally, the parameters governing the dynamics of the credibility stock and its signal are presented in Table 7. We simulate three scenarios: (i) no endogenous credibility; (ii) high credibility; and (iii) low credibility. In the baseline scenario, η_1 is set to one, eliminating any scope for endogenous credibility in our model. For the subsequent two scenarios, η_1 is set to 0.80, representing a credibility stock can vary over time and is persistent. The inflation target is calibrated to the midpoint of Peru's target range ($\bar{\pi} = 2.00$) and the high inflation level for the pessimistic model is set to the upper bound of the target range ($\pi_H = 3.00$). Then, the second scenario, representing high trust in the monetary authority, is achieved by setting $\eta_2 = 0.25$. At last, the third scenario, representing low credibility, is characterized by η_2 takes the value of 1.

Table 5. *Parameters estimated by IRF Matching*

	Parameters	Value
Potential GDP	$\Omega^{f/p}$	-0.3982
Ouput Gap	$\Omega^{f/y}/\Omega_y^{f/p}$	-0.0398 / 0.0398
Inflation Expectations	$\Omega^{f/exp}$	0.2844
Inflation of Food and Energy - Persistence	$\lambda^{f/ae}$	0.5058
Inflation of Food and Energy - Sensitivity	$\Omega^{f/ae}$	2.8368

Table 6. *ICEN: ARMA(3,4) parameters*

AR Parameters	Value	MA Parameters	Value
α_0	-0.2521	β_1	0.8058
α_1	0.3029	β_2	1.3588
α_2	-0.7739	β_3	0.7796
α_3	0.4105	β_4	0.3289

[9] We partially confirm this calibration by computing impulse response functions (IRFs) to the trend and cycle components from the application of a one-sided HP filter to the non-primary GDP. The cumulative effects on the cycle are 0.11 of the total effects on the trend.

Figure 7. *IRF Matching*

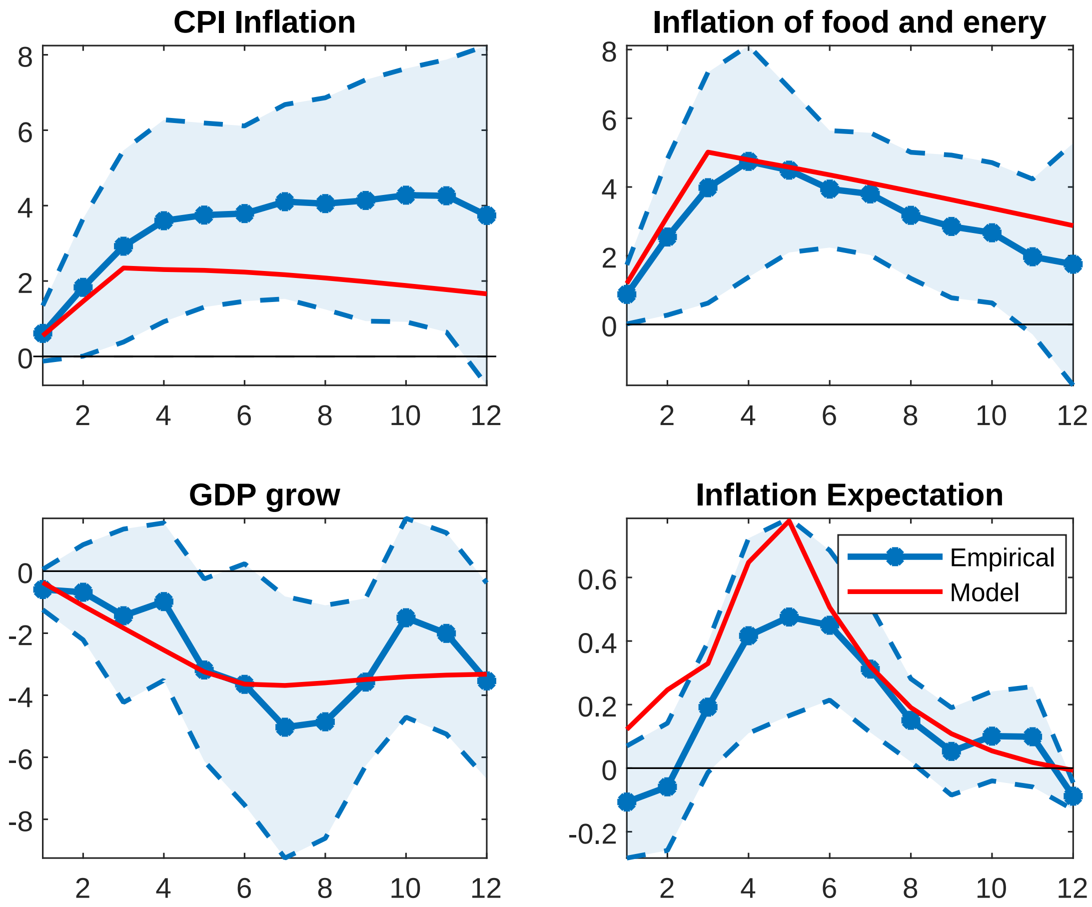


Table 7. *Credibility block parameters*

Parameter	No end. cred.	High cred.	Low cred.
η_1	1.00	0.80	0.80
η_2	0.00	0.25	1.00
π_H	3.00	3.00	3.00
$\bar{\pi}$	2.00	2.00	2.00
ρ_L/ρ_H	0.50	0.50	0.50

4.4 Results

In our model, El Niño affects the economy through nonlinear mechanisms, leading to: (i) disruptions in economic activity by impacting both potential GDP and the output gap, and (ii) inflationary pressures due to fluctuations in food and energy prices, as well as inflation expectations. Figure 8 shows the impulse responses of key macroeconomic variables to an ENSO shock generated by this framework[10].

Each panel in Figure 8 shows the dynamic response of a macroeconomic variable to such an event. Additionally, the figure presents three different parameterizations of the interest rate response to inflation deviations, as defined by the Taylor rule coefficient, ϕ_π. Given the qualitative similarity of the macroeconomic responses across parameterizations,

[10] We characterize the shock by an ICEN index exceeding 1.7 for two consecutive quarters and remaining above 1 for an additional quarter. This configuration represents an El Niño event of strong or greater intensity.

we first analyze the general shape of the responses and leave the examination of their quantitative variations for an exercise with repeated ENSO shocks.

Following the shock, GDP growth declines while inflation initially increases, mainly due to rising food and energy prices. Interestingly, the transmission mechanisms of El Niño result in distinct persistence patterns for its negative effects on potential GDP and the output gap. The immediate and substantial decline in GDP growth primarily reflects the response of potential GDP growth, which reverts to its pre-shock level after ten quarters. Conversely, the output gap experiences a smaller initial increase due to a more rapid decline in potential output relative to aggregate demand. Following one quarter, the output gap begins to contract, exhibiting more persistent effects due to El Niño's spillover impacts on aggregate demand. Regarding inflation, the trajectory and magnitude of core inflation closely align with the response of inflation expectations, contributing to a prolonged effect of the ENSO shock on headline inflation. To manage inflationary pressures and stabilize the economy, the central bank responds by increasing the policy interest rate. The monetary tightening yields an exchange rate appreciation, which helps to dampen inflationary pressures by reducing the cost 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, an El Niño event is unique in that it directly impacts the output gap, potential GDP, inflation of food and energy and inflation expectations through nonlinear mechanisms, introducing new challenges for the formulation of monetary policy.

To provide insights on 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 conduct a simulation exercise were ENSO shock occurs repeatedly. 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 fluctuations in the output gap.[11]

Table 8 provides a numerical illustration of the trade-off monetary policy faces, when stabilizing inflation and the output gap, after successive ICEN shocks. [12]. The table evaluates the loss function under different monetary policy stances (as captured by varying the sensitivity of the Taylor rule to inflation, ϕ_π), at varying frequencies and magnitudes of El Niño events (represented by the variance of the ICEN shock, σ^2_{ICEN}), and at three different levels of credibility (accomplished by setting different values for the parameter η_2).

For each of the three levels of credibility, 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 of this parameter indicates a more aggressive monetary policy response to inflation deviations. Additionally, for a given monetary policy stance, we consider three possible values for the standard deviation of the ICEN shock ($\sigma_{ICEN} = 0.5$, $\sigma_{ICEN} = 1$

[11] 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 $\alpha = 0.048$

[12] In this simulation exercise we consider only ICEN shocks

- the baseline - and $\sigma_{ICEN} = 2$), each representing a different shock intensity. These variations capture changes in the frequency and magnitude of El Niño events. Therefore, each cell in the table shows the average outcome derived from 10^3 simulations over a 20-year period, based on each specified parameter setting.

When the ENSO shock standard deviation is low ($\sigma_{ICEN} = 0.50$), the loss function value is close to 0 for any value of ϕ_π, indicating no cost in stabilizing the economy. At low variance levels of the ICEN shocks, the frequency of El Niño events with a magnitude exceeding the value of 1 is small (1.28 percent of the time), which prevents a significant activation of nonlinear effects.

As the shock standard deviation increases to the baseline calibration ($\sigma_{ICEN} = 1.0$), the loss function rises for all values of ϕ_π and for every level of credibility. This reflects a higher incidence of El Niño in the economy and its non-linear effects. For this calibration, the ENSO occurs on average 8.47% of the time (around 6 quarters out of 80) and it reaches strong ENSOs in 3.23% of the time (approximately 2 quarters out of 80). This frequency is sufficient to gauge significant welfare loss for all values of ϕ_π. It can be seen in Table 8 that the variances of the key macroeconomic variables increase considerably. For example, in the case with no endogenous credibility, the volatility of the nominal interest rate increases from 0.010 when $\phi_\pi = 1.2$ to 0.21 when $\phi_\pi = 1.5$, and reaches 0.23 when $\phi_\pi = 2.0$. Consequently, overall uncertainty in the economy increases substantially. And since the utilized loss function is derived for a simple economy, it is probable that the welfare loss implied by the loss function is underestimated.

Further, when the ICEN standard deviation doubles the baseline calibration ($\sigma_{ICEN} = 2$), the overall uncertainty of the economy and the loss function become significantly greater. In this case, ENSO materializes 15.91% of the time (12 quarters out of 80) and reaches strong ENSOs 11.32% of the time (9 quarters out of 80). At this frequency, the loss function rises sharply, highlighting the importance of the nonlinear effects of ENSO shocks.

Notice that, For $\sigma_{ICEN} = 2$, where El Niño events are more frequent and intense, still a more reactive central bank to the inflation rate (higher ϕ_π) leads to a decrease in the loss function. The reduction in the loss function is primarily due to a larger decrease in inflation volatility compared to the increase in GDP volatility. Furthermore, the decrease in inflation volatility is also reflected in the volatility of inflation expectations, which more than compensates for the increase in the volatility of variables related to economic activity. These reactions suggest that, in the face of significant supply shocks like ICEN, a stronger emphasis on controlling inflation is only possible after more economic instability. Also, as shown in Figure 8, output gap and foreign exchange depreciation display 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.

However, the nonlinear effects of ENSO shocks are accentuated or attenuated by the credibility of the monetary authority. In the case of no endogenous credibility, the persistent propagation mechanism of ENSO shocks to inflation is only due its direct effects in inflation expectations. The central bank reacts to the higher inflation by increasing the interest rate. However, with endogenous credibility, the ENSO shock induces an inflation bias, generate a loss of credibility, which increases the weight of the backward-looking component of inflation expectations which further rises inflation expectations.

In the low credibility case, still a more aggressive monetary policy help to stabilize the economy if various episodes of strong and severe El Niño occurs ($\sigma^2_{enso} = 2$). However, the lack of credibility increases the welfare losses in the economy, as the overall volatility increases. In this scenario, the central bank struggles to manage inflation expectations due to a lack of trust from economic agents. When repeated ENSO shocks occur, the inflation expectation becomes highly volatile as agents doubt the central bank´s ability to control inflation, and higher current inflation influence higher expectations. In this scenario, the central bank is forced to be more aggressive, as a more dovish monetary policy stance implies a higher loss of credibility overtime that will require more interest rate adjustments to control inflation. For example, for $\sigma_{ICEN} = 2$, , the volatility of the interest rate decreases from 6.83 to 5.83 as ϕ_π increases from 1.2 to 2.0.

In the high credibility scenario, the central bank's strong reputation helps anchor inflation expectations, even in the presence of large ENSO shocks. While inflation expectations may still be somewhat elevated compared to the case of perfect credibility, they remain significantly more stable than in the low credibility scenario. For example, the volatility of the interest rate is more than three times higher than in the case without endogenous credibility, but it remains substantially lower than in the low credibility case. With high credibility the benefits of adopting a more hawkish monetary policy become most apparent, particularly as El Niño episodes grow more frequent, with notable improvements in the loss function.

These results indicate that the credibility of the central bank act as a complement instrument for the effectiveness of conventional monetary policy, and a good communication strategy, can be more important the presence these large shocks.

Figure 8. *Semi-Structural model: Effects of El Niño on the peruvian macroeconomy*

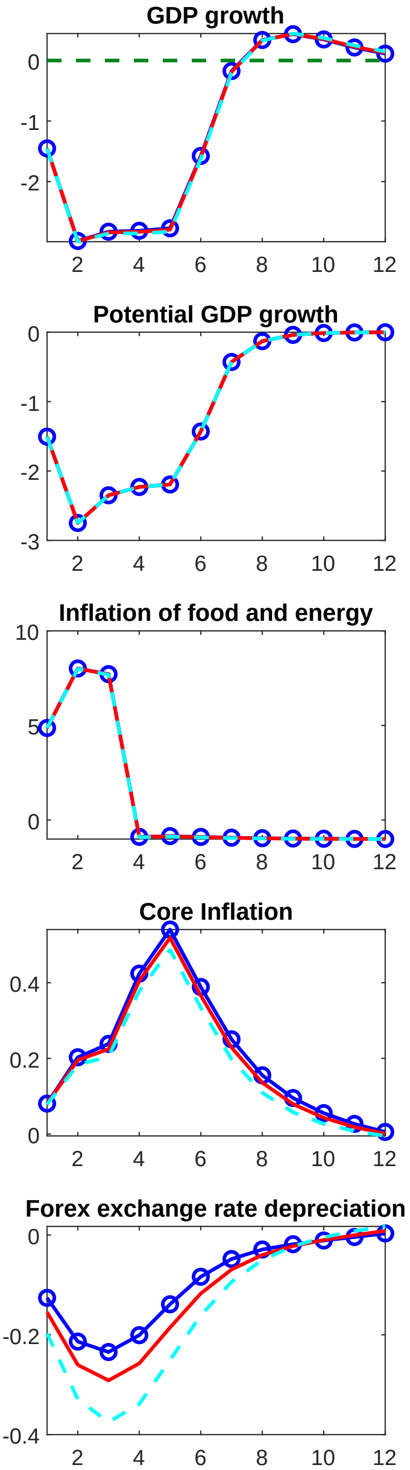


Table 8. *Uncertainty, loss function and monetary policy stance*

ϕ_π	1.20			1.50			2.00		
σ^2_{ENSO}	0.50	1.00	2.00	0.50	1.00	2.00	0.50	1.00	2.00
ENSO>1	1.28%	8.47%	15.91%	1.28%	8.47%	15.91%	1.28%	8.47%	15.91%
ENSO>1.7	0.05%	3.23%	11.32%	0.05%	3.23%	11.32%	0.05%	3.23%	11.32%
				No Endogenous credibility case: Perfect credibility					
Π^e	0.01	0.31	0.96	0.01	0.29	0.89	0.01	0.27	0.81
π^{sae}	0.01	0.23	0.71	0.01	0.21	0.63	0.01	0.18	0.54
i	0.01	0.19	0.61	0.01	0.21	0.66	0.01	0.23	0.72
λ	0.01	0.19	0.61	0.01	0.21	0.65	0.01	0.23	0.72
π^m	0.01	0.14	0.47	0.01	0.15	0.49	0.01	0.16	0.52
π^{ae}	0.64	3.05	6.97	0.64	3.04	6.92	0.64	3.02	6.86
π	0.287	1.430	3.354	0.287	1.416	3.302	0.286	1.399	3.240
y	0.020	0.228	0.651	0.021	0.241	0.692	0.021	0.258	0.745
$\mathcal{L}$	0.082	2.047	11.271	0.082	2.008	10.924	0.082	1.962	10.522
				Low credibility case					
Π^e	0.11	1.85	7.17	0.10	1.51	5.69	0.09	1.20	4.41
π^{sae}	0.09	1.57	6.10	0.08	1.24	4.70	0.07	0.94	3.48
i	0.10	1.70	6.83	0.11	1.60	6.25	0.12	1.53	5.83
λ	0.10	1.70	6.81	0.11	1.59	6.23	0.12	1.52	5.81
π^m	0.08	1.30	5.53	0.08	1.18	4.89	0.09	1.09	4.38
π^{ae}	0.64	3.13	7.14	0.64	3.07	6.88	0.64	3.01	6.65
π	0.301	1.956	5.454	0.299	1.787	4.736	0.296	1.638	4.118
y	0.025	0.222	0.746	0.022	0.223	0.629	0.022	0.291	0.857
$\mathcal{L}$	0.091	3.827	29.776	0.089	3.196	22.445	0.088	2.687	16.991
				High credibility case					
Π^e	0.04	0.71	2.80	0.04	0.63	2.38	0.03	0.54	1.99
π^{sae}	0.03	0.58	2.31	0.03	0.49	1.90	0.03	0.41	1.50
i	0.04	0.57	2.36	0.04	0.59	2.33	0.05	0.61	2.35
λ	0.04	0.57	2.35	0.04	0.58	2.32	0.05	0.61	2.34
π^m	0.03	0.43	1.84	0.03	0.43	1.77	0.03	0.43	1.72
π^{ae}	0.64	3.10	7.19	0.64	3.06	7.03	0.64	3.03	6.87
π	0.289	1.576	4.079	0.289	1.528	3.826	0.288	1.478	3.584
y	0.021	0.198	0.515	0.021	0.228	0.630	0.021	0.266	0.778
$\mathcal{L}$	0.084	2.485	16.649	0.083	2.338	14.659	0.083	2.188	12.877

Notes: [a] The ENSO frequency is calibrated via σ_{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 π, π^{sae}, and Π^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 λ and Λ^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.

5 Conclusion

We leverage 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 persistent supply shocks.

The unique nature of El Niño, with its direct and indirect nonlinear effects on the output gap, potential GDP, food and energy inflation, core inflation, and inflation expectations, introduces additional complexities for monetary policy. Furthermore, the nonlinear effects of these extreme supply shocks become increasingly prominent if they become more frequent: repeated ENSO shocks alter the way agents form their expectations, making the impact of each hit on the economy increasingly severe. Our results indicate that hawkish monetary policy still influences the stabilization of inflation dynamics following large supply shocks such as El Niño. This is true even in the case of low credibility, although to a lesser degree.

In a framework where monetary policy lacks credibility as defined by Chang (1998), large and persistent supply shocks can significantly impact long-term economic stability through an additional credibility channel. This diminished credibility of monetary policy authorities raises the cost of stabilizing the economy. These challenges call for a more nuanced approach to monetary policy, where traditional tools may need to be adjusted to effectively stabilize both inflation and economic activity. Relying on unconventional tools may also be effective. Communication strategies can act as a monetary policy tool by enhancing credibility and managing expectations [13]. Therefore, careful calibration of the monetary policy strategy is essential to minimize adverse effects on both inflation and real economic activity.

In the face of more frequent El Niño events, traditional monetary policy may become less effective, necessitating the exploration of complementary or alternative policy measures. Fiscal policy is one such alternative, offering a valuable means to address significant and persistent supply shocks, although it may also lead to unintended consequences[14]. Other potential strategies include targeted transfers, price controls, contingency planning, and the establishment of precautionary funds. However, a detailed analysis of these and other policies is beyond the scope of this paper.

The future research agenda should focus on developing models that more accurately capture the impact of large climate shocks like El Niño and exploring how policy makers can adapt their strategies to manage these unique challenges while ensuring economic stability.

[13] SeeGoy et al. (2022).

[14] See, for example, Auclert et al. (2023b)

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.

Angrist, J. D., Jordà, , and Kuersteiner, G. M. (2018). Semiparametric estimates of monetary policy effects: String theory revisited. *Journal of Business & Economic Statistics*, 36(3):371–387.

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. (2023a). Managing an energy shock: Fiscal and monetary policy. *National Bureau of Economic Research Working Paper Series*.

Auclert, A., Monnery, H., Rognlie, M., and Straub, L. (2023b). Managing an energy shock: Fiscal and monetary policy. Technical report, National Bureau of Economic Research.

Auerbach, A. J. and Gorodnichenko, Y. (2012). *Fiscal Multipliers in Recession and Expansion*, pages 63–98. University of Chicago Press.

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*.

BCRP (1992). Memoria 1992.

BCRP (2014). Memoria 2014.

BCRP (2017). Reporte de inflación: Panorama actual y proyecciones macroeconómicas 2017-2019.

BCRP (2023). Memoria 2023.

Benes, M. J., Clinton, K., George, A., John, J., Kamenik, O., Laxton, M. D., Mitra, P., Nadhanael, G., Wang, H., and Zhang, F. (2017). *Inflation-forecast targeting for India: An outline of the analytical framework*. International Monetary Fund.

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.

Chang, R. (1998). Credible monetary policy in an infinite horizon model: Recursive approaches. *journal of economic theory*, 81(2):431–461.

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*.

Goy, G., Hommes, C., and Mavromatis, K. (2022). Forward guidance and the role of central bank credibility under heterogeneous beliefs. *Journal of Economic Behavior & Organization*, 200:1240–1274.

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.

Jordà, O., Singh, S. R., and Taylor, A. M. (2024). The Long-Run Effects of Monetary Policy. *The Review of Economics and Statistics*, pages 1–49.

Jordà, O. and Taylor, A. M. (2016). The Time for Austerity: Estimating the Average Treatment Effect of Fiscal Policy. *The Economic Journal*, 126(590):219–255.

Jordà, O. and Taylor, A. M. (2024). Local Projections. NBER Working Papers 32822, National Bureau of Economic Research, Inc.

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.

Piger, J. M. and Stockwell, T. (2023). Differences from differencing: Should local projections with observed shocks be estimated in levels or differences? Working papers, SSRN.

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*.

Tenreyro, S. and Thwaites, G. (2016). Pushing on a string: Us monetary policy is less powerful in recessions. *American Economic Journal: Macroeconomics*, 8(4):43–74.

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

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

Appendices

A Bias in Local Projections

For simplicity, assume a local projection regression without the non-linear feature in Section 3.3, that is, A.1:

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

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,

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

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

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

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 A.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 A.1 yields

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

If $\hat{\gamma}_h$ comes from the estimation of A.1, from A.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 ε in A.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,

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

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

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

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 A.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.

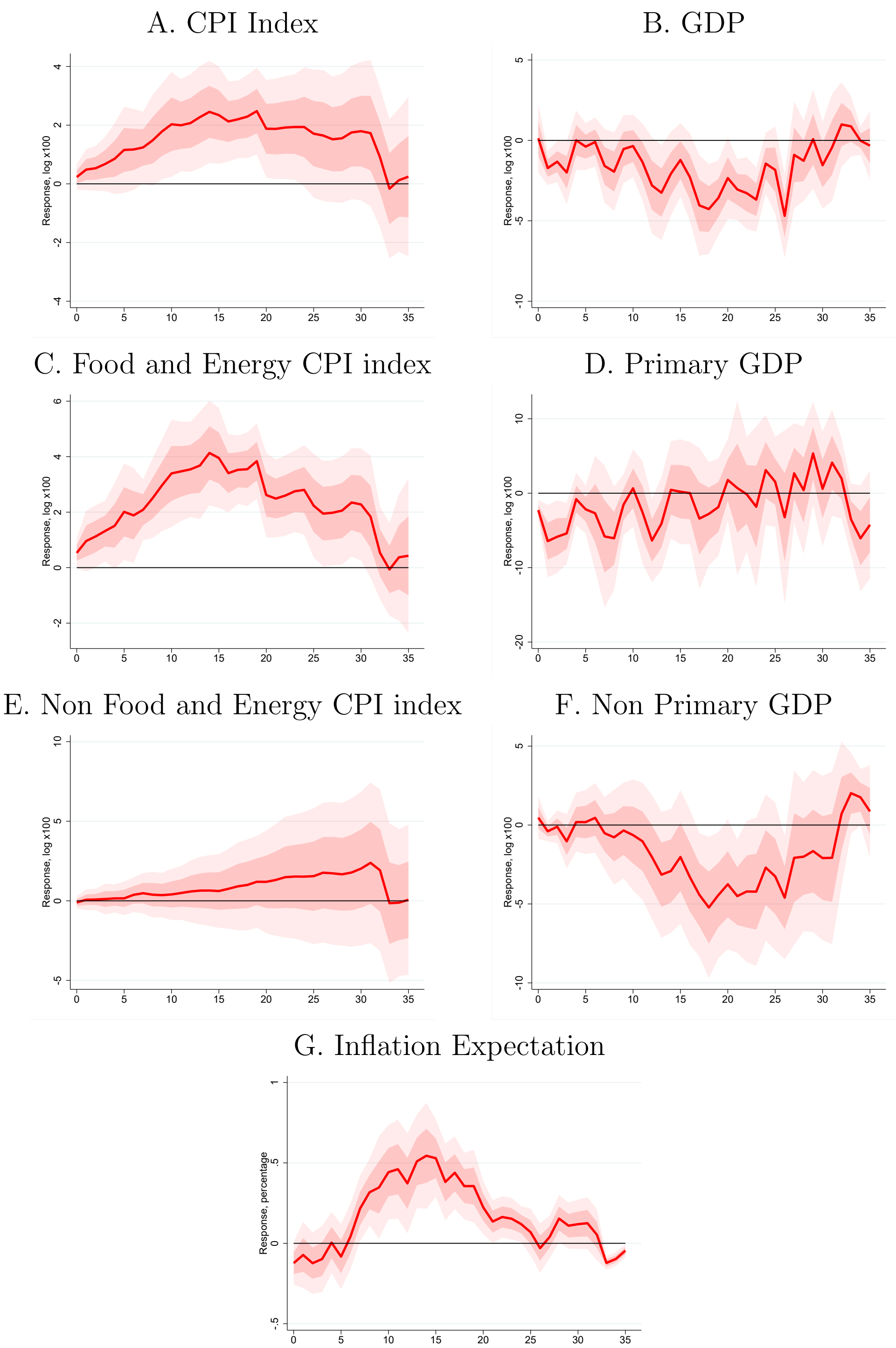
A consequence of the lag structure is that the ENFEN effects, $\{\gamma_{1,h}\}_{h\leq H}$, can be estimated only one month after the event materializes.

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

B Robustness to Local Projections Estimation

B.1 LP Monthly Estimation

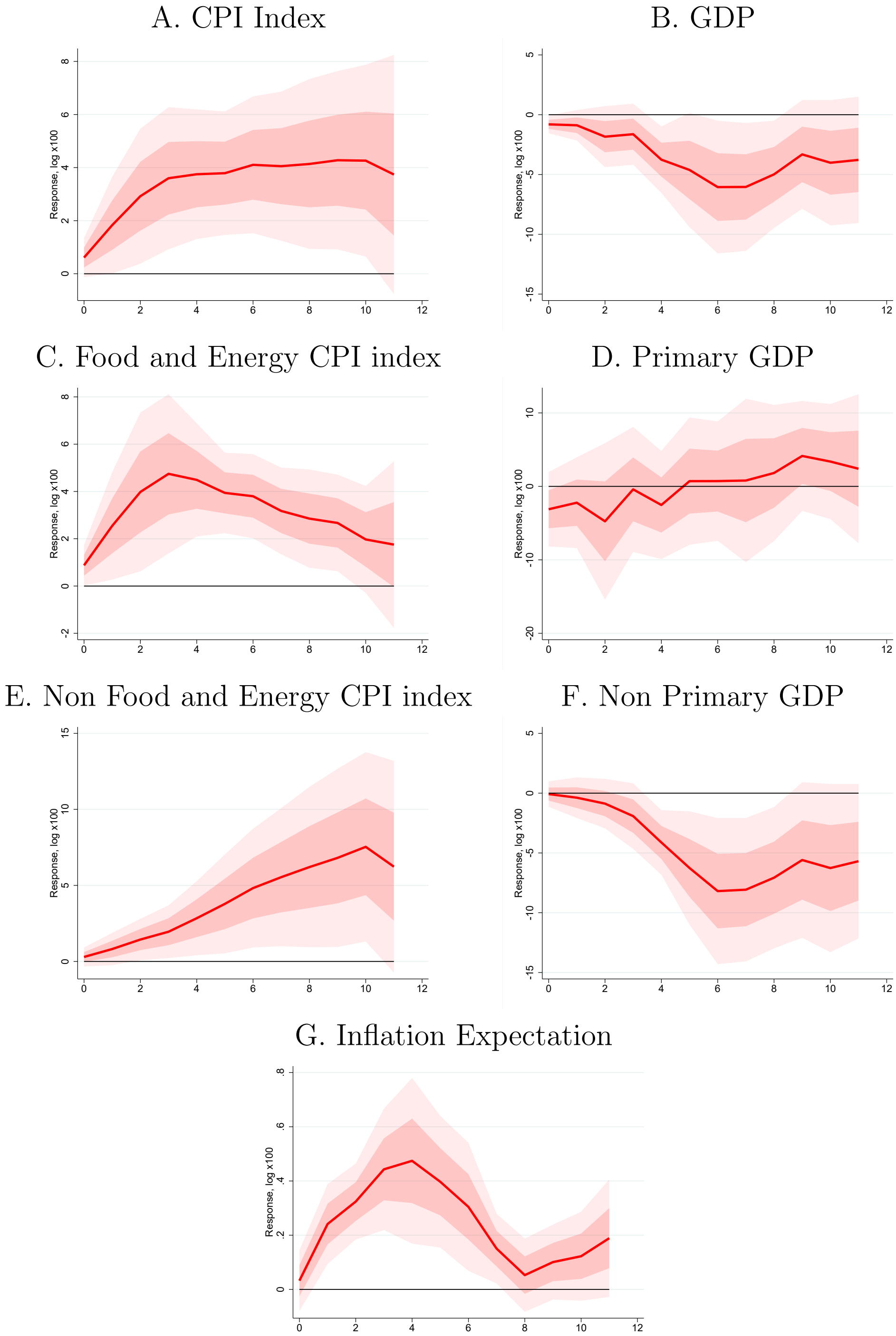
Figure 9. *LP: Monthly Effects of El Niño on aggregate macroeconomic variables*



Note: LP impulses to an ICEN shock, provided the initial ICEN index value is greater than 1. Strong El Niño event (see the main text). y-axis: In Panels A to F the outcome is the cumulative change of 100 times the log of the variable; and Panel G the outcome is the change of inflation expectations. x-axis: Months after the shock. Red shaded areas are one and two standard deviation pointwise confidence bands using heteroscedasticity robust standard errors. Sample 1994m01–2019m12.

B.2 LP Estimation with Sample Post COVID-19 Pandemics

Figure 10. *LP: Quarterly Effects of El Niño on aggregate macroeconomic variables with sample post COVID-19 pandemics*



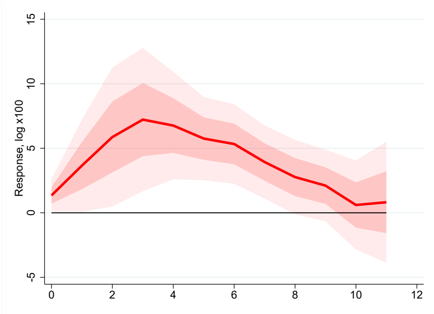
Note: LP impulses to an ICEN shock, provided the initial ICEN index value is greater than 1. Strong El Niño event (see the main text). Estimates from monthly LP estimates. y-axis in Panels A to F the outcome is the cumulative change of 100 times the log of the variable. The variable is the 3-month moving average of the price or GDP index. Only the last month of each quarter is depicted. y-axis in Panel G the outcome is the change in inflation expectations. The quarterly response of inflation expectations is as a 3-month moving average of the monthly impulse responses. x-axis: quarters after the shock. Red shaded areas are one and two standard deviation pointwise confidence bands using heteroscedasticity robust standard errors. Sample 1994m01–2024m10.

B.3 LP Estimation for 3-digit CPI Components

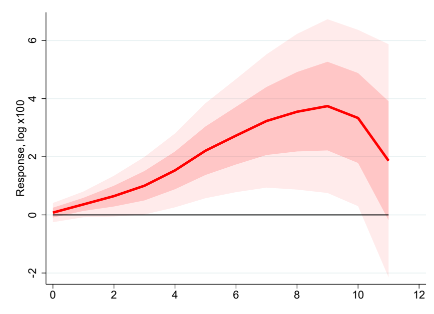
Figure 11. *LP: Quarterly Effects of El Niño on 3-digit CPI components*

Food and Energy CPI index

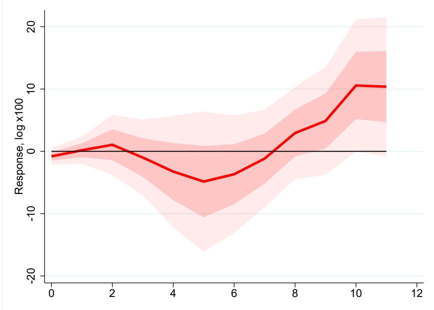
A. Food and beverages at home



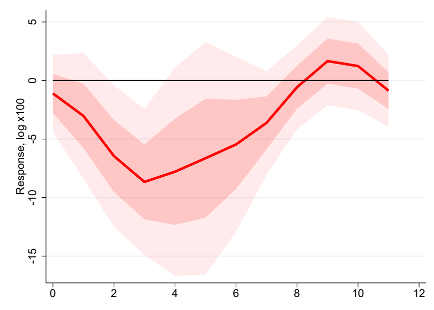
B. Food away from home



C. Energy commodities

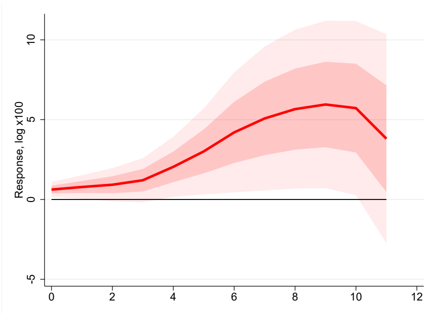


D. Electricity

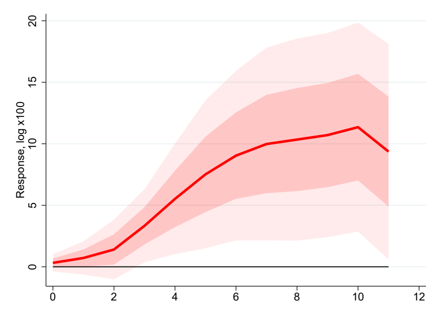


Non Food and Energy CPI index - Goods

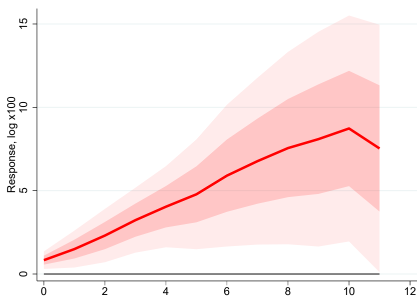
E. Apparel



F. Household Appliances

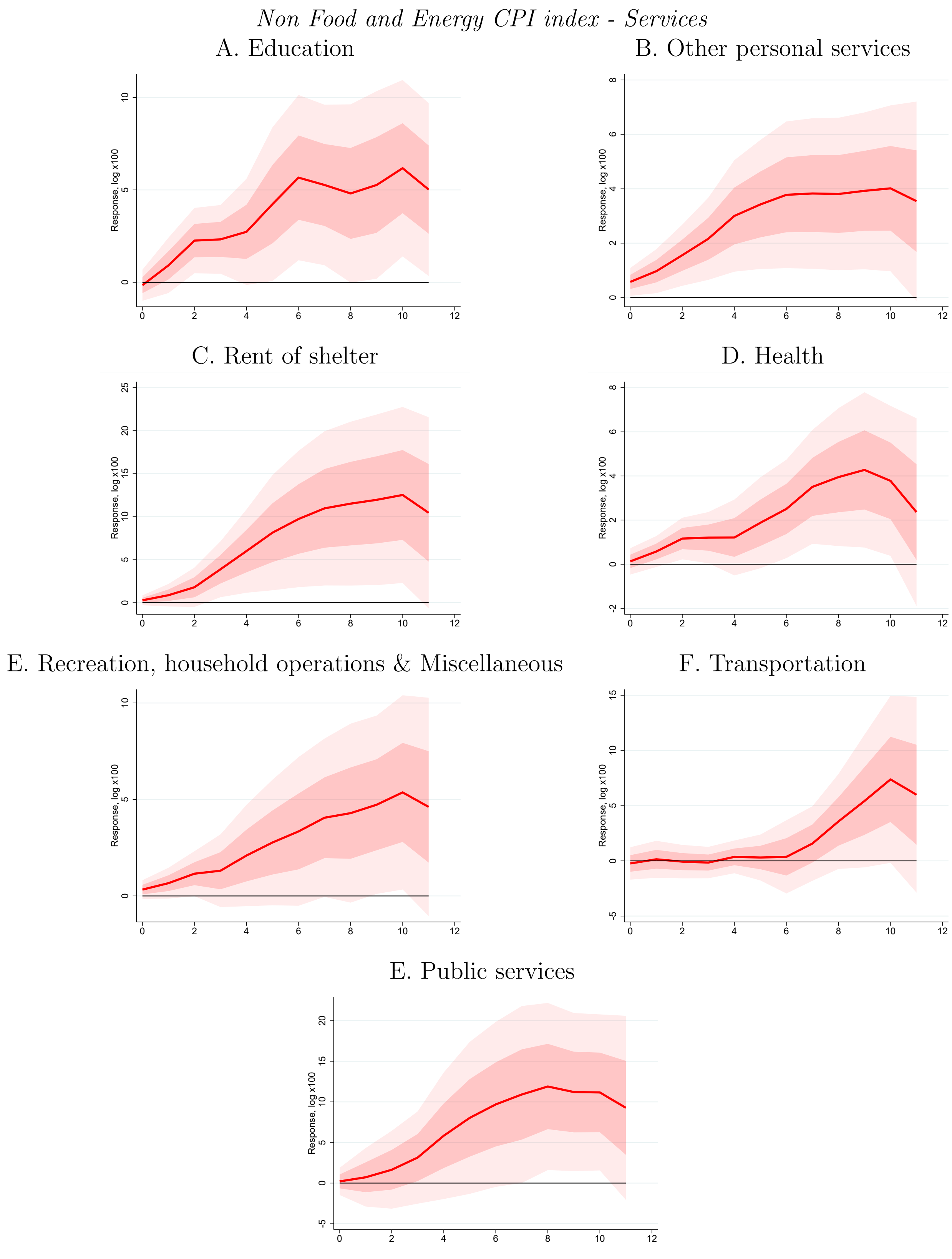


E. Furnishings, Supplies, Transportation and Recreation commodities



Note: LP impulses to an ICEN shock, provided the initial ICEN index value is greater than 1. Strong El Niño event (see the main text). Estimates based on monthly data. y-axis is the cumulative change of 100 times the log of the price index. The variable is the 3-month moving average of the price index, with only the last month of each quarter displayed. Red shaded areas are one and two standard deviation pointwise confidence bands using heteroscedasticity robust standard errors. Sample 1994m01–2019m12.

Figure 12. *LP: Quartely Effects of El Niño on 3-digit CPI components*



Note: LP impulses to a one-degree change in 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). Estimates based on monthly data. y-axis is the cumulative change of 100 times the log of the price index. The variable is the 3-month moving average of the price index, with only the last month of each quarter displayed. Red shaded areas are one and two standard deviation pointwise confidence bands using heteroscedasticity robust standard errors. Sample 1994m01–2019m12.

C Robustness to Empirical Results

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

C.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:

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

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 Ω_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:

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

where A_t denotes the contemporaneous coefficients matrix and Σ_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 (C.1):

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

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, Σ_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 α_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 (C.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).

C.2 A Threshold BVAR Approach

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

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

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:

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

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:

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

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

with A_i as a lower triangular matrix and Σ_t as a matrix defined by:

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

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

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

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.:

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

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 α (Canova and Pérez Forero, 2015).

Finally, log-volatility λ_t enters both in the mean (with lags) and in the covariance matrix Ω_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:

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

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 Θ 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:

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

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.

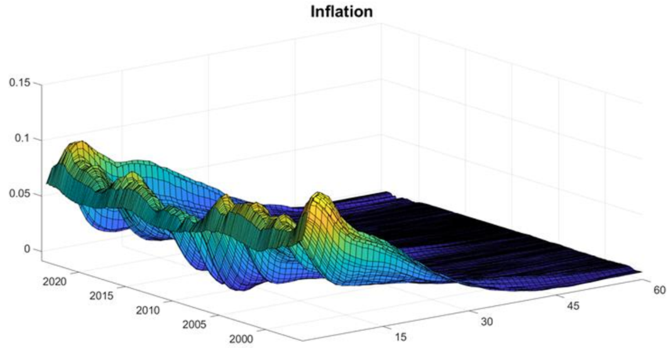
Results

Figure 13 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.

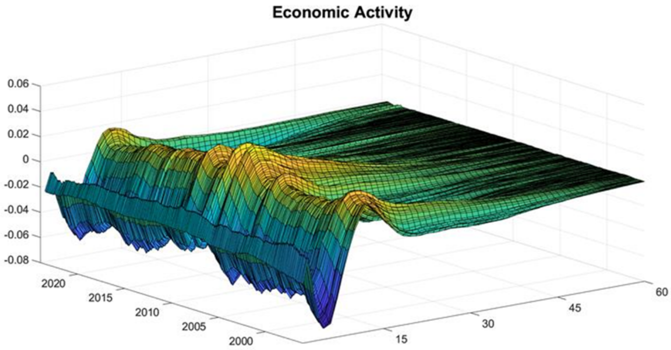
In panel A and B of Figure 13, the surface plots show how the impulse responses of inflation and economic activity evolved over time following a shock in the ICEN index. It is generally observed that positive temperature shocks cause an increase in inflation and contraction in GDP over time. The most pronounced responses correlate with severe El Niño episodes, specifically those in 1998, 2017, and most recently, 2022-2023.

Figure 13. *TVP-VAR-SV: ICEN shock and median value responses of inflation and economic activity (1995-2023)*

Panel A



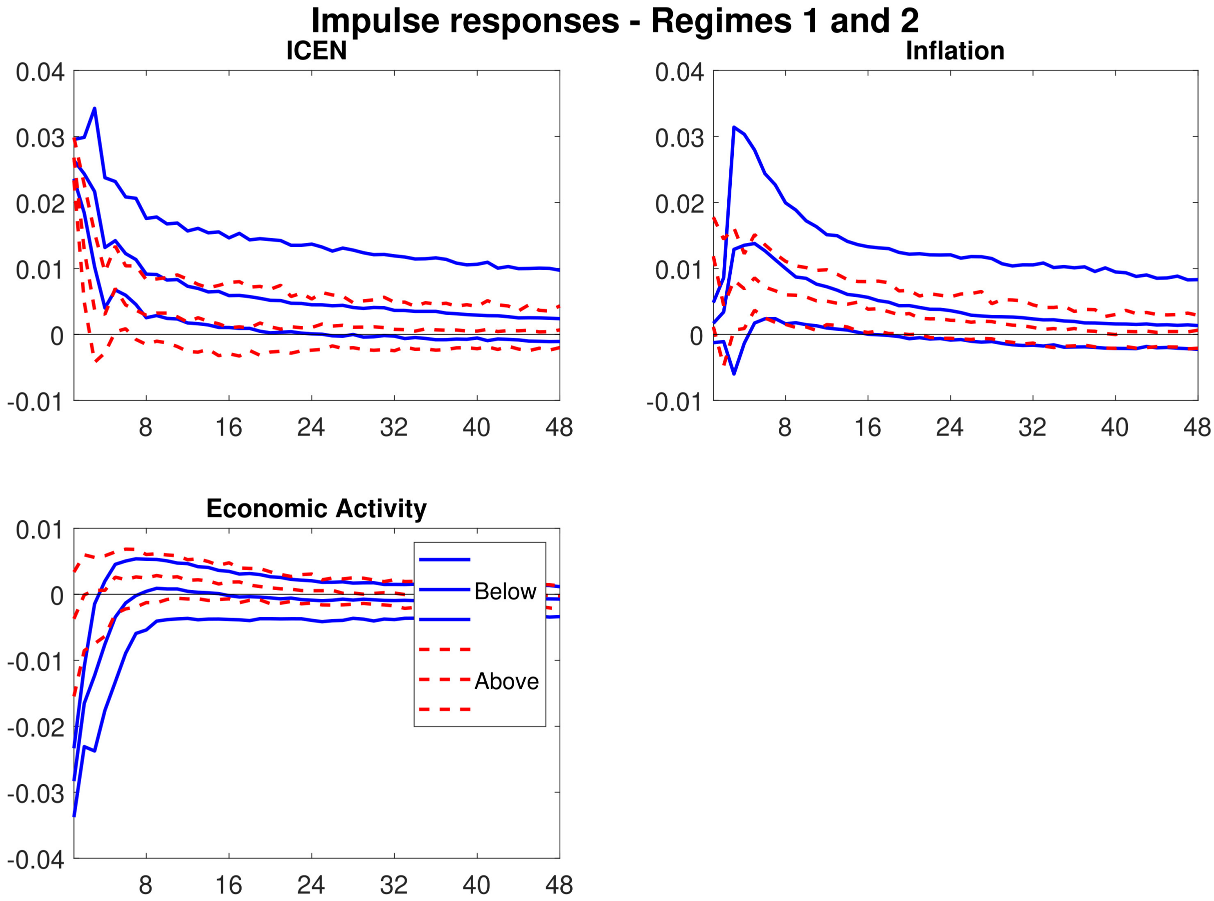
Panel B



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.

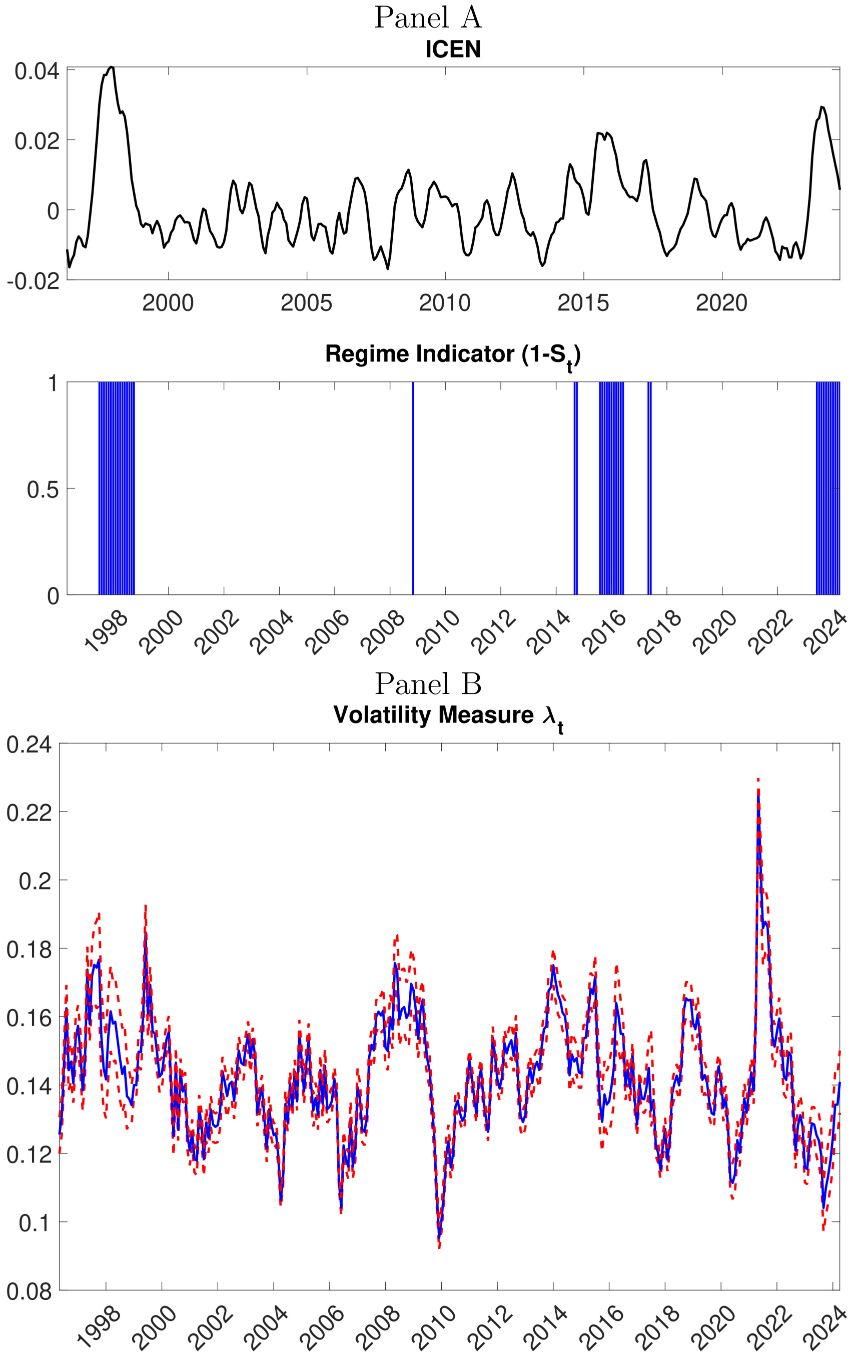
Figure 14 illustrates the impulse responses within the Threshold BVAR model. We find that there are potential differences in the responses to shocks in the ICEN variable, depending on whether the initial conditions are below or above the threshold. Notably, because the model is nonlinear, shocks starting below the threshold tend to be more amplified, potentially triggering a regime switch within the forecast horizon.

Figure 14. *Threshold-BVAR-SV: ICEN shock and median value responses of inflation and economic activity)*



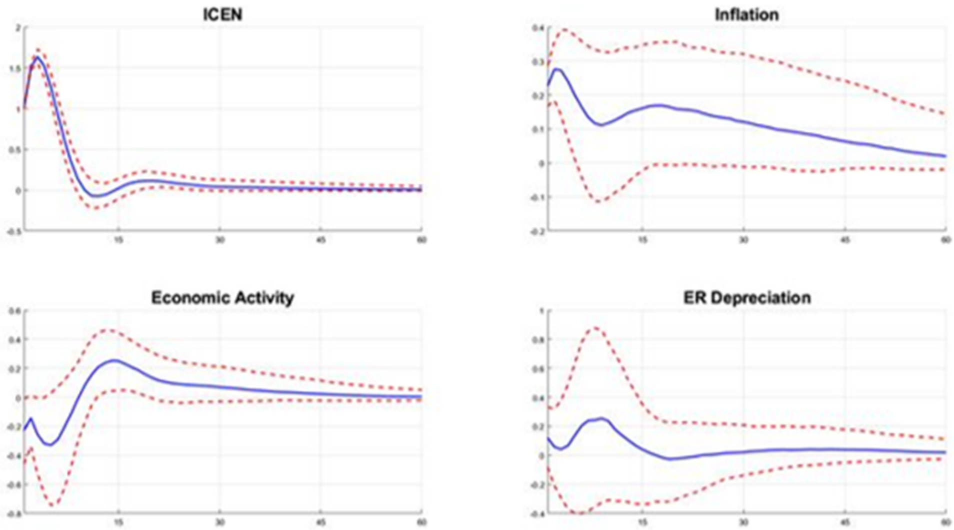
In addition, the model identifies regime switches for temperatures above 1 on the ICEN index, as it is depicted by Figure 15, panel A. The identified periods coincide with the dates when the El Niño phenomenon manifested most intensely. We also control for Stochastic Volatility in means, a very useful component when working with data that has outliers, such as the period associated with the COVID-19 pandemic (see panel B).

Figure 15. *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 16 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 LP impulse responses in Section 3.3, in terms of direction, size, and persistence.

Figure 16. *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.

D Semi-Structural Nonlinear Model

D.1 The Model

The ENSO index

$$ICEN_t = \alpha_0 + \sum_{j=1}^{3} \alpha_j ICEN_{t-j} + \varepsilon_t + \sum_{j=1}^{4} \beta_j \varepsilon_{t-j}, \qquad \epsilon_t \sim N(0, \sigma_f^2) \tag{D.1}$$

GDP Growth and Potential GDP Growth

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

$$\begin{aligned} \Delta Y_t^p = {} & (1-\lambda^p)\Delta Y + \lambda^p \Delta Y_{t-1}^p + -\Omega^{f/p} \left[I_{(ICEN_t>1.7)} ICEN_t + \dots \right. \\ & \dots + I_{(ICEN_{t-1}>1.7)} ICEN_{t-1} + I_{(ICEN_{t-2}>1.7)} ICEN_{t-2} \\ & \left. \dots + I_{(ICEN_{t-3}>1.7)} ICEN_{t-3} + I_{(ICEN_{t-4}>1.7)} ICEN_{t-4} \right] + \varepsilon_t \end{aligned} \tag{D.3}$$

Inflation

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

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

$$\pi_t^{ae} = (1-\lambda^{f/ae})\left[b_s \pi_t^{sae} + (1-b_s)\pi_t^m \right] + \lambda^{f/ae} I_{(ICEN_t>1)} \pi_{t-1}^{ae} + \dots \tag{D.6}$$

$$\dots + \Omega^{f/ae} \left[I_{(ICEN_t>1)} ICEN_t \right] \varepsilon_t \tag{D.7}$$

$$\Pi_t^{ae} = (\pi_t^{ae} + \pi_{t-1}^{ae} + \pi_{t-2}^{ae} + \pi_{t-3}^{ae})/4 \tag{D.8}$$

$$\pi_t = c_{sae}\pi_t^{sae} + (1-c_{sae})\pi_t^{ae} \tag{D.9}$$

$$\Pi_t = (\pi_t + \pi_{t-1} + \pi_{t-2} + \pi_{t-3})/4 \tag{D.10}$$

$$\begin{aligned} \Pi_t^e = {} & \lambda_{\Pi^e}\Pi_{t-1}^e + (1-\lambda_{\Pi^e})\left[c_{\pi^e} C_{t-1} E_t \Pi_{t+4}^{sae} + (1-c_{\pi^e})\Pi_{t-1} \right] \dots \\ & \dots + (1-C_{t-1})\left[\Pi_{t-1} - Meta \right] + \Omega^{f/exp} I_{(ICEN_{t-3}>1.7)} ICEN_{t-3} + \varepsilon_t \end{aligned} \tag{D.11}$$

$$\widehat{\Pi}_t = E_t \Pi_{t+4}^{sae} - Meta \tag{D.12}$$

$$\pi_t^m = c_{mm}\pi_{t-1}^m + (1-c_{mm})E_t\Pi_{t+4}^m + c_{mq}\left[\pi_{t-1}^{m\$} + \lambda_{t-1} - \pi_{t-1}^m \right] + \varepsilon_t \tag{D.13}$$

$$\Pi_t^m = (\pi_t^m + \pi_{t-1}^m + \pi_{t-2}^m + \pi_{t-3}^m)/4 \tag{D.14}$$

Credibility Stock and Signal

$$C_t = \eta_1 C_{t-1} + (1-\eta_1)s_t \tag{D.15}$$

$$s_t = 1 - \eta_2 \frac{(\epsilon_t^L)^2}{(\epsilon_t^H)^2 + (\epsilon_t^L)^2} \tag{D.16}$$

$$\epsilon_t^H = \Pi_t - [\rho_H \Pi_{t-1} + (1-\rho_H)\pi_H] \tag{D.17}$$

$$\epsilon_t^L = \Pi_t - [\rho_L \Pi_{t-1} + (1-\rho_L)\bar{\pi}] \tag{D.18}$$

$$s_t = 1 \quad \text{if} \quad \epsilon_t^L < 0 \tag{D.19}$$

$$s_t = 0 \quad \text{if} \quad \epsilon_t^H > 0 \tag{D.20}$$

Interest rates in local currency

$$i_t = \rho_i i_{t-1} + (1-\rho_i)\left[i_t^n + f_\pi \widehat{\Pi}_t + f_y \left[c_{fy} y_t + (1-c_{fy}) y_{t-1}\right]\right] + \varepsilon_t \tag{D.21}$$

$$i_t^n = (1-\rho_{i^n})i + \rho_{i^n} i_{t-1}^n + \varepsilon_t \tag{D.22}$$

$$i_t^{mn} = i_t + \varepsilon_t \tag{D.23}$$

$$R_t^{mn} = i_t^{mn} - \Pi_t^e \tag{D.24}$$

$$R_t^{mn/eq} = Z_t^{mn} + cY_{mn}\left[\Delta Y_{t+1}^p - \Delta Y\right] + cR_{mn}\left[\Delta Y_{t+1}^{*/p} - \Delta Y^*\right] + \varepsilon_t \tag{D.25}$$

$$Z_t^{mn} = c_{zmn} Z_{t-1}^{mn} + (1-c_{zmn}) R^{mn} + \varepsilon_t \tag{D.26}$$

$$r_t^{mn} = R_t^{mn} - R_t^{mn/eq} \tag{D.27}$$

Interest rates in foreign currency

$$i_t^{me} = i_t^* + \varepsilon_t \tag{D.28}$$

$$R_t^{me} = i_t^{me} - \Pi_t^e + \Lambda_t^e \tag{D.29}$$

$$R_t^{me/eq} = Z_t^{me} + cY_{me}\left[\Delta Y_{t+1}^p - \Delta Y\right] + cR_{me}\left[\Delta Y_{t+1}^{*/p} - \Delta Y^*\right] + \varepsilon_t \quad \text{(D.30)}$$

$$Z_t^{me} = c_{zme} Z_{t-1}^{me} + (1 - c_{zme}) R^{me} + \varepsilon_t \quad \text{(D.31)}$$

$$r_t^{me} = R_t^{me} - R_t^{me/eq} \quad \text{(D.32)}$$

Exchange Rate

$$\lambda_t = \rho_\lambda E_t \lambda_{t+1} + (1+\rho_\lambda)\left[i_t^{me} + \xi_t - i_t^{mn} + \varepsilon_t\right] \quad \text{(D.33)}$$

$$\Lambda_t = (\lambda_t + \lambda_{t-1} + \lambda_{t-2} + \lambda_{t-3})/4 \quad \text{(D.34)}$$

$$\Lambda_t^e = \rho_{\lambda^e} \Lambda_{t-1}^e + (1 - \rho_{\lambda^e})\Lambda_{t+4} + \varepsilon_t \quad \text{(D.35)}$$

$$\xi_t = \xi_t^{eq} + \varepsilon_t \quad \text{(D.36)}$$

$$\xi_t^{eq} = (1 - \rho_\xi)\xi + \rho_\xi \xi_{t-1}^{eq} + \varepsilon_t \quad \text{(D.37)}$$

$$Q_t = \pi_t^* + \lambda_t - \pi_t \quad \text{(D.38)}$$

$$q_t = q_{t-1} + \frac{Q_t - Q_t^{eq}}{4} \quad \text{(D.39)}$$

$$Q_t^{eq} = \rho_Q q_t + \varepsilon_t \quad \text{(D.40)}$$

Output gap and its determinants

$$\begin{aligned} y_t = {} & a_{y^e}\left[x_t^e + y_{t-1}\right] + a_y y_{t-1} + a_\psi \psi_{t-1} + a_\tau \tau_t + a_q q_t + a_{y^*} y_t^* + \ldots \\ & a_t t_t + a_g g_t - \Omega^{f/y} I_{(ICEN_t>1)} ICEN_t + \Omega_y^{f/p} I_{(ICEN_t>1.7)} ICEN_t + \varepsilon_t \end{aligned} \quad \text{(D.41)}$$

$$x_t^e = \rho_{x^e} x_{t-1}^e + (1 - \rho_{x^e})\left[E_t y_{t+1} - y_{t-1}\right] + \varepsilon_t \quad \text{(D.42)}$$

$$\psi_t = -\left[c_r^{mn} r_t^{mn} + c_r^{me} r_t^{me} + c_{hb}(\xi_t - \xi_t^{eq})\right] \quad \text{(D.43)}$$

$$t_t = \rho_t t_{t-1} + \varepsilon_t \quad \text{(D.44)}$$

$$g_t = \rho_g g_{t-1} + \varepsilon_t \quad \text{(D.45)}$$

$$T_t = \rho_T T_{t-1} + \varepsilon_t \quad \text{(D.46)}$$

$$\tau_t = (a_{\tau_{largo}} + a_{\tau_{corto}})\tau_{t-1} - a_{\tau_{largo}} a_{\tau_{corto}} \tau_{t-2} + (a_{\tau_{largo}} - a_{\tau_{corto}})\frac{T_t}{4} + \varepsilon_t \quad \text{(D.47)}$$

Foreign economy

$$\pi_t^* = b_\pi^* \pi_{t-1}^* + (1-b_\pi^*) E_t \Pi_{t+4}^* + b_y^* y_{t-1}^* + \varepsilon_t \tag{D.48}$$

$$\Pi_t^* = (\pi_t^* + \pi_{t-1}^* + \pi_{t-2}^* + \pi_{t-3}^*)/4 \tag{D.49}$$

$$\pi_t^{m\$} = (1-c_{\pi^{m\$}})\pi_t^{*\$} + c_{\pi^{m\$}} \pi_{t-1}^{*\$} + \varepsilon_t \tag{D.50}$$

$$i_t^* = \rho_i^* i_{t-1}^* + (1-\rho_i^*) \left[i_t^{*n} + f_\pi^* (E_t \Pi_{t+4}^* - \pi^*) + f_y^* y_t^* \right] + \varepsilon_t \tag{D.51}$$

$$i_t^{*n} = (1-\rho_{i^n}) i^* + \rho_{i^n} i_{t-1}^{*n} + \varepsilon_t \tag{D.52}$$

$$R_t^* = i_t^* - \Pi_{t+4}^* \tag{D.53}$$

$$R_t^{*/eq} = Z_t^* + cY^* \left[\Delta Y_{t+1}^{*/p} - \Delta Y^* \right] \tag{D.54}$$

$$Z_t^* = (1-\rho_{Z^*}) R^* + \rho_{Z^*} Z_{t-1}^* + \varepsilon_t \tag{D.55}$$

$$r_t^* = R_t^* - R_t^{*/eq} \tag{D.56}$$

$$\Delta Y_t^* = y_t^* - y_{t-4}^* + \Delta Y_t^{*/p} \tag{D.57}$$

$$\Delta Y_t^{*/p} = (1-\rho_{\Delta Y^{*/p}}) \Delta Y^* + \rho_{\Delta Y^{*/p}} \Delta Y_{t-1}^{*/p} + \varepsilon_t \tag{D.58}$$

$$y_t^* = a_{Ey}^* y_{t+1}^* + a_y^* y_{t-1}^* - a_r^* r_{t-1}^* + \varepsilon_t \tag{D.59}$$

Previous volumes in this series

1275 July 2025	Decoding climate-related risks in sovereign bond pricing: a global perspective	Sofia Anyfantaki, Marianna Blix Grimaldi, Carlos Madeira, Simona Malovana and Georgios Papadopoulos
1274 July 2025	Incorporating physical climate risks into banks' credit risk models	Vasily Pozdyshev, Alexey Lobanov and Kirill Ilinsky
1273 June 2025	Global portfolio investments and FX derivatives	Tsvetelina Nenova, Andreas Schrimpf and Hyun Song Shin
1272 June 2025	Financial conditions and the macroeconomy: a two-factor view	Marco Jacopo Lombardi, Cristina Manea and Andreas Schrimpf
1271 June 2025	Monetary policy and earnings inequality: inflation dependencies	Jaanika Meriküll and Matthias Rottner
1270 May 2025	Stablecoins and safe asset prices	Rashad Ahmed and Iñaki Aldasoro
1269 May 2025	Expecting job replacement by GenAI: Effects on workers' economic outlook and behavior	Yusuke Aoki, Joon Suk Park, Yuya Takada and Koji Takahashi
1268 May 2025	Towards verifiability of total value locked (TVL) in decentralized finance	Pietro Saggese, Michael Fröwis, Stefan Kitzler, Bernhard Haslhofer and Raphael Auer
1267 May 2025	Collateralized lending in private credit	Iñaki Aldasoro and Sebastian Doerr
1266 May 2025	Exchange Rate Effects on Firm Performance: A NICER Approach	Nuwat Nookhwun, Jettawat Pattararangrong and Phurichai Rungcharoenkitkul
1265 May 2025	DeFiying gravity? An empirical analysis of cross-border Bitcoin, Ether and stablecoin flows	Raphael Auer, Ulf Lewrick and Jan Paulick
1264 April 2025	Inflation cycles: evidence from international data	Alberto Americo, Douglas K G Araujo, Johannes Damp, Sjur Nilsen, Daniel Rees, Rafael Schmidt and Christian Schmieder
1263 April 2025	Fragile wholesale deposits, liquidity risk, and banks' maturity transformation	Carola Müller, Matias Ossandon Busch, Miguel Sarmiento and Freddy Pinzon-Puerto

All volumes are available on our website www.bis.org.