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ENSO Climate Patterns on Global Economic Conditions

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Abstract

We investigate the role of ENSO climate patterns on global economic conditions. The estimated model is based on a rich and novel monthly dataset for 20 economies, capturing 80.2% of global output (based on 2021 IMF data) over the period 1999:01 to 2022:03. The empirical evidence from an estimated global vector autoregression with local projections (GFAVLP) model links an El Niño (EN) shock with higher output and inflation, corresponding with lower global economic policy uncertainty (GEPU). While a shock to the world oil and food price is inflationary, a food price shock leads to elevated GEPU, more so during a LN shock. A main finding is that an increase of the food price can be a source of global vulnerability. The findings indicate that the weather shock impact on global economic conditions is dependent on the climate state. Our result undermines existing studies connecting climate change and economic damage via statistical approach.

Highlights:

- We investigate the transmission of climate shocks on global economic conditions.
- We distinguish between an EN and a LN climate states.
- An EN and a LN shock corresponds with higher consumer price and food inflation, albeit a food price shock elevates GEPU during a LN state.
- Our results undermine studies connecting climate change and economic damage via statistical approach.

JEL Classification: C32, F44, O13, Q54.

Keywords: Weather; Oil and Food Prices; Global Macroeconometric Modeling; and Economic Policy Uncertainty.

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1 Introduction

Two grievances are frequently directed towards the economics profession. On the one hand, economists give little importance to climate issues (e.g., Oswald and Stern, 2019a, Oswald and Stern, 2019b, Noah, 2021), on the other hand, they underestimate the importance of climate effects on the economy (e.g., Nordhaus, 1994; Dietz and Stern, 2015; DeFries et al., 2019; Pezzey, 2019; Stern and Stiglitz, 2021).

An existing strand of literature has sought to establish the impact of climate on economic activity (Tol, 2009) and has reached the conclusion that climate change impact on activity would be rather limited (Tol, 2018).

Yet, interest in this issue has been renewed by IPCC's publications, which have highlighted several possible temperature increase scenarios (see Stocker et al., 2014 for a presentation of different greenhouse gas Representative Concentration Pathway, translated into global temperature trajectories) Economists have sought to use observed climate-growth relation to project future temperature impact on GDP in terms of growth (e.g., Burke et al., 2015) or levels (e.g. Newell et al., 2021).

However, these approaches are not without debate. The existing literature points to two main limitations:

First, the studies focus on average annual temperatures or precipitation, whereas it is extreme events that cause the most damage to activity. This is particularly an issue because climate change can be seen as a change in events distribution, i.e. moving to a fat tailed distribution (Field et al., 2012).

Second, when future temperature is projected to be outside the historical conditions observed for a country, the authors use variation observed today across *countries* to infer climate variation over *time*, (a critique expressed by Tol (2018) and Woillez et al. (2020)) However, such a projection does not take into account the cost of adapting infrastructures or the depreciation of present investments (Bolton et al., 2020). In other words: projecting the temperature of one country today onto another country tomorrow does not really make sense.

This paper addresses a third limitation: we show that the impact of weather shocks on global activity is a function of climate. Therefore, the impact of weather shocks on activity within today's climate cannot be used to infer weather shocks impact on activity with tomorrow's climate. The reason is that the transmission channel of weather shocks on activity are dependant on climate.

We propose a new analytical framework to study the effect of climate on economic activity. We rely on the the Equatorial Southern Oscillation Index (ESOI) as a measure of the ENSO climate phenomenon (see Dufrénot et al. (2021)). This allows us to distinguish between an EN and a LN climate state. Therefore our study does not suffer from a projection bias, neither across *time*, nor *space*. On the contrary, we observe that the effect of extreme climate events on activity depends on climate.

This paper explores the global dimensions of changing weather patterns and the international oil and food commodity prices as they affect economic conditions. This research overlaps with three strands of literature. The first strand relates to a voluminous body of literature analyzing the effects that changing oil prices have on the macroeconomy (e.g., Hamilton, 1983, Hamilton, 2008, Kilian, 2009, Bodenstein et al., 2011, Kilian, 2014, Kang et al., 2017, Arouri et al., 2014, You et al., 2017, among others). Commodity prices (in real terms) tend to be endogenous and pro-cyclical to the global business cycle (e.g., Kilian, 2009, Kilian and Zhou, 2018). Kilian, 2009 distinguishes between demand and supply shocks in the oil price, and finds that increases in the oil price since 2003 are primarily driven by demand. The similar increases in the food price has raised concerns about inflationary pressures. This is finding is also confirmed by Joëts et al., 2017 for corn, soybeans and wheat. This identification is consistent with Alquist and Kilian, 2010, who finds that the oil price is determined endogenously and simultaneously.

The second strand relates to economic uncertainty. In recent years, numerous researchers have analyzed the effects that commodity prices have on uncertainty. The majority have focued on understanding the influence of oil prices (e.g., Kang and Ratti, 2013b, Antonakakis et al., 2014, Hailemariam et al., 2019) and economic policy uncertainty (EPU), a measure developed by Baker et al. (2016) as an indicator of economic uncertainty. Ginn et al. (2021) investigate the transmission of the international oil and food price on EPU for the case of India. These authors find that international prices can create a spillover effect on the domestic economy. Uncertainty can also have consequential effects on the macroeconomy relating to firm-investmentment (e.g., Kang et al., 2014, Handley and Limao, 2015), stock prices (e.g., Kang and Ratti, 2013a, Antonakakis et al., 2013, You et al., 2017) and unemployment (e.g., Caggiano et al., 2014, Caggiano et al., 2017). Ginn (2022) finds that a natural disaster may create a disturbance which can spill over into aggregate uncertainty such that EPU increases (decreases) during an expansionary (non-expansionary) state.

The third strand relates to only a handful of papers to address the transmission that weather shocks has on economic conditions (Brunner, 2002, Cashin et al., 2017, De Winne and Peersman, 2018 and Peersman, 2018).

Brunner (2002) finds that weather shocks has important and statistically important effects on global commodity prices. Cashin et al. (2017) estimates a global vector autoregression to investigate weather shocks for twenty-one country/regions. Cashin et al. (2017) find heterogeneous responses of a weather shocks with regard to output growth. Peersman (2018) find that food price shocks can explain 30% inflation volatility in euro area. De Winne and Peersman (2018) show that increases in global agricultural commodity prices that are caused by unfavorable harvest shocks in other regions of the world can curtail domestic economic activity.

This paper provides three main contributions to the literature. First, using a rich dataset for nine economies representing circa two-thirds of global output[1], we analyze to what extent a global El Niño weather and commodity price shock transmit a disturbance on the global factor economy. This paper is based on monthly data over the period 1999:01 to 2022:03, which has the potential benefit of capturing the short-term temporal effect that weather has on the economy (e.g., Barnston (2015)), as opposed to using quarterly data as in previous studies (Brunner (2002), Cashin et al. (2017)). By adding oil and food prices with changing weather conditions to the model, we can explore the global linkages that weather has on these two commodities.

The main contribution of our study is that we incorporate a weather shock transmission channel to the economy. A weather shock that occurs during EN periods brings immediate increase in food price inflation, which later translates into consumer price inflation and, following monetary policy reactions, leads to higher interest rate in the medium run (1 year). The same weather shock occurring during LN periods would lead to a lagged increase in food prices. Consequently, we do not observe second-round effect on consumer prices and the interest rate remains flat. Therefore we can conclude that extreme weather events are transmitted to the economy through different transmission channels depending on the climate state.

This result is particularly important because it invalidates the statistical evaluation method mentioned above, used by researchers to predict the effect of climate change on the economy (Tol 2009 and Tol 2018). Indeed, the transmission of an extreme weather event on the economy depends on climate, so we cannot use an estimated relationship between weather and economy for a given climate to project it on a future climate: this relationship will no longer exist, the channels of transmission will be heterogenous. Our results corroborate Woillez et al. (2020) who perform an *ad absurdum* demonstration of the limitation of studies connecting climate change and economic damage though a statistical approach.

Our paper contributes to an important literature on ENSO economic impacts (see Smith and Ubilava, 2017, Cashin et al., 2017, Atems and Sardar, 2021)

First, we start from a rich data-set to construct a set of global indicators using a large dataset of a time-varying weighted indexation (based on GDP). While previous studies generally focus on one commodity (e.g. Tack and Ubilava (2015) on cotton) or a given country (e.g. Ubilava (2012) on Colombia), Mueller and Osgood (2009) on Brazil or Mainardi (2011) on Burkina Faso and Niger, we add to the literature by showing that the effects of ENSO operate at the global level.

Second, rather than estimating the partial influence of a partial weather shock in isolation (Brunner (2002) and Cashin et al. (2017) estimate the transmission of only an EN weather shock), we employ a GFAVLP which allows us to cast the entire data via changing ENSO states. Second, this paper employs a global factor augmented vector error correction model (GVARLP) framework to assess the transmission of shocks on economic uncertainty. As the impact of El Niño cannot be reduced to one country, but rather relates to global climate patterns, this paper exploits a global factor model framework which paves the way to understand how climate affects the global economic conditions.

The global structure allows an identification such that oil and food prices are treated endogenously. This framework is an extension of GVAR (Cashin et al., 2017), where the model structure partially facilitates an endogenous treatment of oil and non-fuel commodities (based on the US economy). By adding oil and food prices with changing ENSO weather conditions, we explore the global linkages that weather has on these two commodities. The benefit of these contributions allows the estimated economic system to not necessarily remain static within one state of ENSO (EN or LN) conditional that the system has entered into that state. Overall, our model facilitates a way to capture the full data generating process of how the changing ENSO states affect global economic conditions. Incorporating the effects of weather while integrating an endogenous

[1]The 20 economies include: Brazil ("BRA"), Switzerland ("CHE"), Chile ("CHL"), Canada ("CAN"), China ("CHN"), Columbia ("COL"), Czech Republic ("CZE"), Euro zone (19 countries; "EUR"), United Kingdom ("GBR"), Hungary ("HUN"), Ireland ("IRL"), India ("IND"), Israel ("ISR"), Japan ("JPN"), South Korea ("KOR"), Poland ("POL"), Russia ("RUS"), Sweden ("SWE"), Turkey ("TUR") and the United States ("USA"). Based on IMF data in purchasing power parity terms, the nine economies considered in this paper represent 80.2% of global output, see https://www.imf.org/external/datamapper/NGDPD@WEO/EURO/USA/CAN/CHN/CHL/IND/KOR/BRA/WEOWORLD/COL/GBR/CZE/HUN/IRL/ISR/JPN/POL/RUS/TUR/SWE/CHE. The Euro zone values are based on the 19 member countries (i.e., Austria, Belgium, Cyprus, Estonia, Finland, France, Germany, Greece, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, the Netherlands, Portugal, Slovakia, Slovenia, and Spain).

treatment of commodity prices on a global scale is of critical importance to further inform our understanding of the consequential effects of changing climate *ex post*, an area of paramount importance, considering current assessments of future climate scenarios are shrouded in uncertainty.

The rest of the paper is structured as follows: in Section 2 describes the data. Section 3 discusses the global dimensions of the business cycle considered in the paper. The modelling methodology and empirical results are summarized in Section 4. Section 5 summarizes the paper, with an emphasis of the food price as a source of global vulnerability. Section 6 concludes the paper.

2 Data

The model is based on 20 economies and includes seven endogenous variables: weather ($ENSO_t^G$), output growth ($\Delta \ln Y_t^G$), aggregate inflation ($\Delta \ln P_t^G$), oil inflation ($\Delta \ln P_{E,t}^G$), food inflation ($\Delta \ln P_{A,t}^G$), interest rate (R_t^G) and GEPU ($\ln EPU_t^G$). The sample period is monthly which covers 1999:01 to 2022:03.[2] The endogenous variables considered include a weather index; industrial production index[3]; the consumer price index (CPI); the world oil price and food commodity price; the short-term interest rate[4]; and EPU. The data is summarized in Table 1. The exogenous variables includes a global financial crisis (GFC) dummy variable (Hailemariam et al., 2019)[5], CBOE Volatility Index (VIX) and U.S. Infectious Diseases (Baker et al., 2019)[6].

Table 1: Variable Selection

Item	Symbol	Source	Description
ENSO	$ENSO_t^G$	NOAA	Equatorial Southern Oscillation Index
Output	Y_t	OECD/FRED	Industrial Production
Aggregate CPI	P_t^G	OECD	CPI: All items
Oil Price	$P_{E,t}^G$	FRED	Brent Oil Price
Food Price	$P_{A,t}^G$	FRED	World Food Price
Interest Rate	R_t	OECD/FRED	Short-term interest rate
Policy Uncertainty	EPU_t	FRED (see [a])	Global EPU
VIX	VIX_t	FRED	CBOE Volatility Index
Global Financial Crisis	GFC_t	NBER (see [b])	GFC dummy variable
Infectious Disease	$COVID_t$	FRED	U.S. Infectious Diseases tracker

[a]: `https://www.policyuncertainty.com`.
[b]: GFC dummy variable set to 1 between 2007:DEC to 2009:JUN, consistent with the NBER recession dates for the U.S.

All endogenous variables are converted to logarithm with the exception of the real interest rate and weather index. For consistency, output for China and India[7]; the CPI; and EPU are seasonally adjusted via ARIMA X-12 algorithm from the U.S. Census Bureau. The oil and food price data, denominated in U.S. dollars, is deflated by dividing by the U.S. CPI. Economic uncertainty is based on the global EPU data by Davis (2016). The Equatorial Southern Oscillation Index (ESOI) is used as a global measure of weather, which is collected from the National Oceanic and Atmospheric Administration (NOAA).

3 Global Dimensions of the Business Cycle

Four global variables are considered: ENSO climate index, output, CPI, interest rate, oil price, food price and GEPU. Each are discussed in turn.

[2]The choice of economies and sample period combination is, in part, based on data availability. The sample period is quite extensive, while the 20 economies considered represent the majority (80.2%) of global output based on nominal GDP indexed in U.S. Dollars using IMF data. The sample period also overlaps with the commodity price booms that occurred in 2004 (Radetzki, 2006).

[3]For India, manufacturing production index (FRED mnemonic INDPRMNTO01IXOBM) is used as opposed to total production index (FRED mnemonic INDPROINDMISMEI), considering data availability (the correlation between the is 0.9918 for Jan 2000 to Dec 2018). For China, we use total production excluding construction (FRED mnemonic CHNPRINTO01IXPYM). As the production index for China includes missing values, the Kalman smoother using an ARIMA state space representation is used to impute missing values.

[4]For India, the interest rate is based on the 90 day Treasury Bill interest rate (e.g., Patnaik et al. (2011), Gabriel et al. (2012), Saxegaard et al. (2010), Anand et al. (2014) and Ginn and Pourroy (2020a)).

[5]The GFC dummy variable is set to 1 between 2007:12 to 2009:06, consistent with the NBER recession dates for the U.S.

[6]COVID-19 emerged as a pandemic in December 2019 and quickly spread across the world, with far-reaching consequences including higher deaths, stagnation of economic growth and elevated uncertainty, which resulted in lock-downs and other precautions to reduce the spread of the virus.

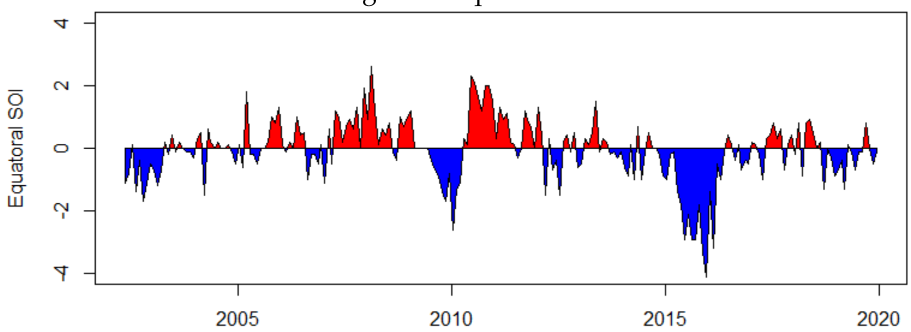
[7]Industrial production for other countries in the sample are already seasonally adjusted.

3.1 Global ENSO Weather Patterns

When a major El Niño (La Niña) occurs, there is an anomalous loss (increase) of heat from the ocean to atmosphere so that global mean temperatures rise (fall) (McPhaden et al., 2020). The anomalous atmospheric patterns are known as the Southern Oscillation. El Niño, La Niña Southern Oscillation (ENSO) is one of the most important climate indicators, which has a major influence of global weather conditions (e.g., Ropelewski and Halpert (1987), Rosenzweig et al. (2001), McPhaden et al. (2006) and Dai (2013), Brönnimann et al. (2007)).[8]

ENSO relates to cyclical, environmental conditions that occur across the equatorial Pacific Ocean. Changes to ENSO are due to natural interactions between sea surface temperature, rainfall, air pressure, atmospheric and oceanic circulation. The effects of ENSO, commonly called "teleconnections", emphasize that changing conditions can have a profound effect on global climate, which can in turn directly affect people's livelihoods (e.g., Barlow et al. (2001), Diaz et al. (2001), and Alexander et al. (2002)).

Figure 1: Equatorial SOI



While the Southern Oscillation Index (SOI), which is a commonly used indicator of ENSO, has been used in empirical papers as an indicator of weather as it relates to economic conditions (e.g., Brunner (2002), Cashin et al. (2017)), the Equatorial Southern Oscillation Index (ESOI) is considered in this paper. According to Shi and Su (2020), ESOI is superior to SOI since the former has a stronger correlation with the Niño 3.4 region sea surface temperature anomaly as well as with westerly/easterly wind bursts. Furthermore, Barnston (2015) in a NOAA report suggests that ESOI overcomes two limitations of the SOI. First, SOI is based on the sea level pressure at just two stations (Tahiti and Darwin), which means "it can be affected by shorter-term, day-to-day or week-to-week fluctuations unrelated to ENSO." Second, the SOI is is based on Tahiti and Darwin, both of which are located south of the equator whereas "the ENSO phenomenon is focused more closely along the equator." Taking these facts into consideration, the empirical analysis is based ESOI at monthly frequency (as opposed to quarterly data as in Brunner (2002) and Cashin et al. (2017)). The ESOI is plotted in Figure 1, where red (blue) indicates El Niño (La Niña) conditions.

3.2 Construction of GDP Weighted Global Aggregates

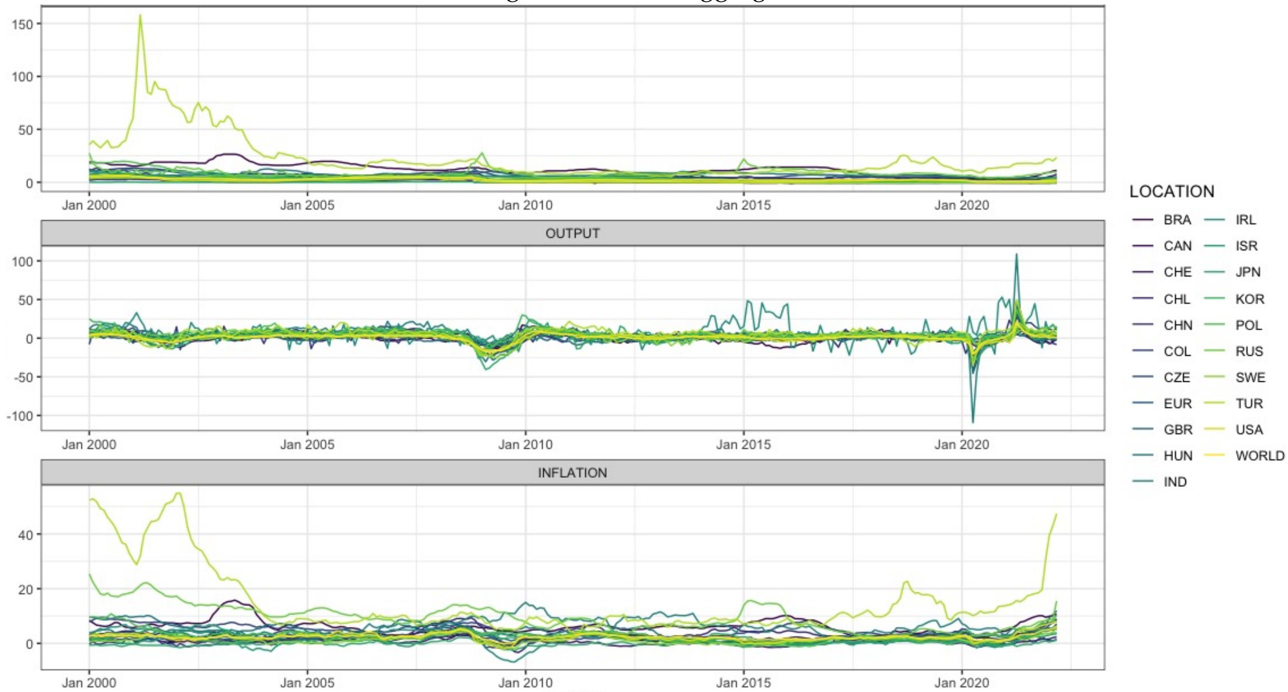
We construct three global economic indicators based on 20 sampled economies using a GDP weighted index. The global indicators include output (industrial production), CPI and interest rate. The weight of each economy in the index is derived from its economic size (proxied using quarterly nominal GDP data), which is accordingly rebased (i.e., sums to one for each period). We then apply the weights to each of the respective global indicators in the respective quarter, considering the data is monthly. Figure 17 in the Appendix shows that the period-to-period movements are quite stable, yet the relationship over a longer period can evolve.

3.3 Global Commodities

The commodities of interest in this study include the international oil and food price. Of the rich literature that considers a commodity price, most papers include the oil price. Our global structure allows an identification such that oil and food prices are treated endogenously. This allows us to analyze the effect that ENSO climate patterns has on important commodity prices.

[8]The NOAA considers ENSO as "one of the most important climatic phenomena on Earth", see https://www.weather.gov/mhx/ensowhat.

Figure 2: Global Aggregates



Since the early 2000s, the world experienced elevated and persistent prices of many commodities relative to the somewhat more tranquil period after the mid-1980s. Several authors have dubbed this phenomena as a commodity price ”super cycle”.[9] Hamilton (2008) motivates an argument of the importance of oil prices; that nine of ten recessions in the US since World War II have been preceded by an increase in oil prices. Yet the same argument can be conveyed for both energy and food prices, at least since the turn of the century on a global scale at the onset of all four recessions (see Figure 3).[10] Kilian and Vigfusson (2017) do not find evidence of a ”mechanical relationship” between an increase in the oil price and recessions.

Figure 3: International Oil and Food Price

Source: FRED (real terms). Shaded areas indicate OECD recession dates for 35 OECD member and non-member economies as proxy for global recession.

3.4 Global EPU

Building on the EPU index by Baker et al. (2016), Davis (2016) constructs a measure of GEPU. The GEPU is considered in the empirical analysis. EPU is negatively correlated with the business cycle (e.g., Bloom, 2009 and Baker et al., 2016). Using our novel dataset, we estimate a linear OLS regression model as follows:

$$\ln EPU_t^G = \alpha + \beta_Y \Delta Y_t^G + \beta_P \Delta P_t^G + \beta_R R_t^G + \beta_{COVID} COVID_t + \gamma \tau_t + u_t \quad (1)$$

[9] For example, Radetzki (2006) identifies the commodity price booms also occurred in the early 1950s, 1973/1974 and 2004 as the start of the third commodity price boom since the second world war.

[10] To illustrate this point, Figure 3 shows the international oil and food price movements against recession dates for 35 OECD member and non-member countries, where latter is used as a proxy for a global recessionary period.

where we consider two models including up to four control variables, which include output growth, aggregate inflation, interest rate and infectious diseases data. The model includes an intercept (α), trend (γ) and an error term (u_t). In Table 2, models (1) and (2) are symmetric except the latter includes the infectious diseases dataset.

Table 2: Empirical Findings (OLS Regression)

	Dependent variable:	
	Global EPU	
	(1)	(2)
α	4.258^{***}	4.272^{***}
	(0.096)	(0.096)
β_P	0.066^{***}	0.058^{***}
	(0.022)	(0.022)
β_Y	-0.023^{***}	-0.020^{***}
	(0.004)	(0.003)
β_R	-0.001^{**}	-0.0004^{*}
	(0.0002)	(0.0003)
β_{COVID}		0.011^{***}
		(0.002)
γ	0.004^{***}	0.004^{***}
	(0.0003)	(0.0004)
Observations	267	267
Adjusted R^2	0.641	0.658
Residual Std. Error	0.284	0.277
F Statistic	119.509^{***}	103.560^{***}

Note: *, ** and *** denote significance at 10%, 5% and 1%, respectively. OLS robust standard errors are presented in parentheses.

The results suggests that GEPU is associate with lower output growth, lower inflation and higher interest rate, where all coefficients are statistically significant. Further, we find that an increase in infectious diseases is positively associated with EPU and is statistically significant. The linear trend is positive and statistically significant for both models.

3.5 Global Variables

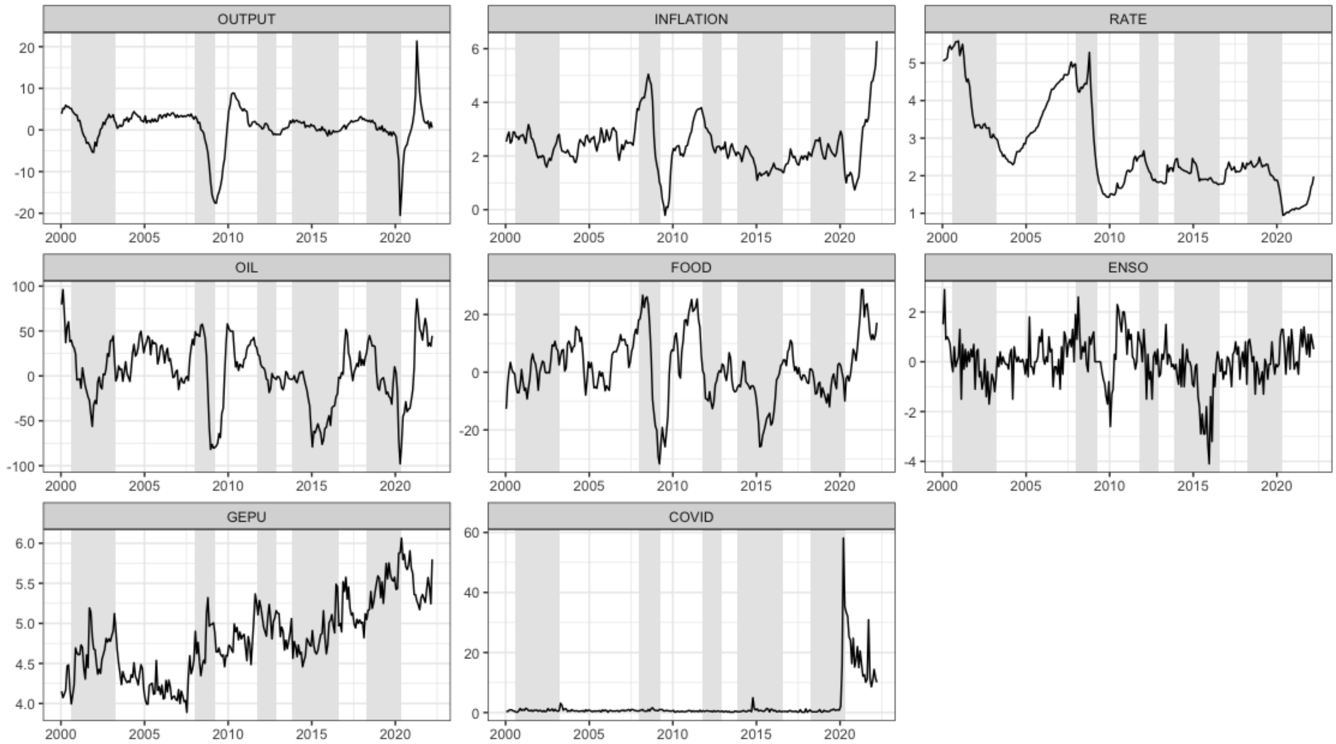
The correlation between global variables (output growth, inflation and interest rate) is provided in Table 3. The correlation for world output growth is quite high with e.g., USA, CAN, EUR and RUS; and somewhat moderate to low for IRL, GBR and CHN. There is moderate to strong correlation between world inflation with the exception of IND, RUS and BRA. The negative correlation for inflation observed between the World (and taking the USA as a secondary benchmark) and IND notably during the GFC and post-COVID.

Table 3: Variable Correlation

Location	$\Delta \ln Y_t^G$	$\Delta \ln P_t^G$	R_t^G
WORLD	1.00	1.00	1.00
BRA	0.74	0.14	0.57
CAN	0.80	0.78	0.96
CHE	0.76	0.73	0.92
CHL	0.59	0.61	0.76
CHN	0.41	0.53	0.50
COL	0.73	0.25	0.84
CZE	0.86	0.70	0.81
EUR	0.95	0.88	0.93
GBR	0.53	0.72	0.93
HUN	0.90	0.45	0.68
IND	0.66	(0.01)	0.08
IRL	0.18	0.67	0.93
ISR	0.56	0.39	0.80
JPN	0.90	0.26	0.58
KOR	0.64	0.59	0.91
POL	0.83	0.49	0.76
RUS	0.77	0.15	0.19
SWE	0.84	0.73	0.84
TUR	0.81	0.19	0.52
USA	0.92	0.90	0.91

Figure 4 plots the global data which shows the global dataset captures two major turning points. The top-pane shows a sizable decline in output which occurred during the GFC[11] and onset of the spread of the COVID-19 virus. There was a noticeable decrease in aggregate inflation and interest rate during these two time periods.

Figure 4: Global Macro Indicators



Shaded areas indicate OECD recession dates (source: FRED). All variables are converted to logarithm with the exception of the interest rate. Output and prices are further converted to year-over-year growth rates. See Table 1 for further details.

4 Methodology and Results

We estimate two models: the first model estimates a GVARLP that includes ENSO, output growth, inflation, interest rate and EPU (henceforth referred to the "baseline" model. The second model extends the baseline model to capture the effects of an international oil and food commodity price (henceforth referred to "extended" model).

The vector autoregression model with local projections (VAR-LP), developed by Jordà (2005), is employed to estimate the dynamic responses that a disaster has on macroeconomic conditions. We estimate a linear and non-linear model. For the non-linear model, we estimate the GVARLP where state dependence is based on ENSO for three reasons. First, ENSO can have important economically important effects on commodities and economic activity (e.g., Brunner, 2002, Cashin et al., 2017, Dufrénot et al., 2021). Second, state dependence facilitates an econometric model that can capture the full data generating process of how changing ENSO states affect global economic conditions.[12] Third, an EN and a LN are two opposing climate patterns where there can be a long length of each episode.[13]

We analyze the impact of weather shocks on the economy according to the climate state. The main difference between climate and weather is the time length at which we look at events. Therefore, we consider two climate states, EN and LN, while we proxy weather by ESOI shocks. Therefore, we plot IRF that show global economic variables reaction to weather shocks (i.e. ESOI shock) according to climate state (i.e EN or LN).

[11] According to the NBER, the recession dates for the U.S. is between 2007:DEC to 2009:JUN.

[12] The existing research (e.g., Brunner, 2002 and Cashin et al., 2017) analyze the partial effects of an El Nino (a La Nina) shock by "shutting off" the La Nina (El Nino) in their specification.

[13] According to NOAA, episodes of EN and LN occur 9 to 12 months, see `https://oceanservice.noaa.gov/facts/ninonina.html`.

4.1 Linear Model

A common representation of a VAR is as follows:[14]

$$\boldsymbol{y_t} = \boldsymbol{\alpha} + B(L)\boldsymbol{y_t} + \boldsymbol{\epsilon_t} \tag{2}$$

where $\boldsymbol{y}_t^T$ is the transpose of a column vector; $\boldsymbol{\alpha}$ is a vector of intercept term; B(L) is an autoregressive lag polynomial; and $\boldsymbol{\epsilon}_t$ is a vector of white noise error terms. Multiplying equation (2) by $\boldsymbol{A}_0$ yields a VAR represented in structural form:

$$\boldsymbol{A}_0\boldsymbol{y_t} = \boldsymbol{\zeta} + \boldsymbol{A_0}B(L)\boldsymbol{y_t} + \boldsymbol{u_t} \tag{3}$$

for $\boldsymbol{\zeta} = \boldsymbol{A}_0\boldsymbol{\alpha}$ and $\boldsymbol{u}_t = \boldsymbol{A}_0\boldsymbol{\epsilon}_t$. Matrix $\boldsymbol{A}_0$ captures the contemporaneous relationship between the variables. To identify $\boldsymbol{A}_0$, a standard Cholseky decomposition is employed imposing a lower triangular matrix. This specification is consistent with Brunner (2002), where ENSO is not influenced contemporaneously by the ENSO state.

The impulse responses corresponding to the reduced form and structural form shocks are, respectively, generalized as follows (Kilian and Kim, 2011):

$$\Phi_h^{VAR} = \sum_{l=1}^{h} \Phi_{h-l}^{VAR} B_l, h \in \{1, 2, ..., H\} \tag{4}$$

and

$$\Theta_h^{VAR} = \Phi_h^{VAR} A_0^{-1}, h \in \{1, 2, ..., H\} \tag{5}$$

An alternative approach to estimate the reduced form impulse responses is to fit a linear projection (baseline model) as follows:

$$\boldsymbol{y}_{t+h} = \boldsymbol{\alpha}_h + \mathbf{B}_1^h \boldsymbol{y}_t + \mathbf{B}_2^h \boldsymbol{y}_{t-1} + ... + \mathbf{B}_p^h \boldsymbol{y}_t + \boldsymbol{\epsilon}_{t+h} \tag{6}$$

where $\boldsymbol{y}_t^T$ is the transpose of a column vector; α_h is an intercept term; $\mathbf{B}_i^h$ are autoregressive coefficients for future horizon h = 1,...,H; and ϵ_{t+h} is a disturbance. As there is serial correlation present in the error terms, the Newey-West correction is used for standard errors. The corresponding structural impulse responses are:

$$\Theta_h^{LP} = \Phi_h^{LP} A_0^{-1}, h \in \{1, 2, ..., H\} \tag{7}$$

where A_0^{-1} is recovered from the estimated model in equation (3) (see Kilian and Kim, 2011).

4.1.1 Baseline Model

The vector of macroeconomic variables for the baseline model includes the following:

$$\boldsymbol{y}_t^T = [ENSO_t^G, \Delta \ln Y_t^G, \Delta \ln P_t^G, R_t^G, \ln EPU_t^G] \tag{8}$$

where $\boldsymbol{y}_t^T$ includes incremental disaster data, output growth, inflation, interest rate and EPU. The model also includes a trend term. In this identification setup, weather is weakly exogenous, i.e. weather conditions do not contemporaneously affect global macroeconomic conditions (Brunner (2002), Cashin et al. (2017), Bastianin et al. (2018)). Brunner (2002) estimates a VAR to investigate ENSO and commodity price shocks. Cashin et al. (2017) estimates a global vector autoregression to investigate weather shocks for twenty-one country/regions. Bastianin et al. (2018) estimate a VAR where weather influences Colombian coffee production, exports and price.

Of the aforementioned authors, the paper by Bastianin et al. (2018) is the only research that considers a symmetric VAR for the Colombian coffee market with regard to both an El Nino and a La Nina weather shock. That is, most papers consider an El Nino shock in isolation. In the linear model, we similarly estimate a symmetric model, which is then extended to a non-linear asymmetric model in Section 4.2. Following Colombo (2013), EPU is order last to ”purge” uncertainty from contemporaneous movement from macroeconomic indicators. We also include the CBOE Volatility Index (VIX) as an exogenous variable.[15]

[14]Note that we abstract from deterministic terms with the exception of the intercept term for expositionary purposes.

[15]VIX is used as a proxy for international financial volatility. While Baker et al. (2016) find positive co-movement between the EPU and VIX, there is ”substantial independent variation” (Baker et al., 2016), where the former index measures uncertainty due to economic policy that is not captured by financial market risk. Pastor and Veronesi (2012) and Pástor and Veronesi (2013) show that while uncertainty and volatility are correlated, the degree to which political signals over time are known can correspond with investors to update their beliefs about potential future policy choices. Similarly, Białkowski et al. (2021) confirm a link between market volatility and policy uncertainty becomes weaker in an environment characterized by opinion divergence among investors and exceptional performance of the stock market. Consistent with Manopimoke et al. (2018), we include the VIX as a control variable for financial market uncertainty, so that EPU will capture the influence of policy uncertainty.

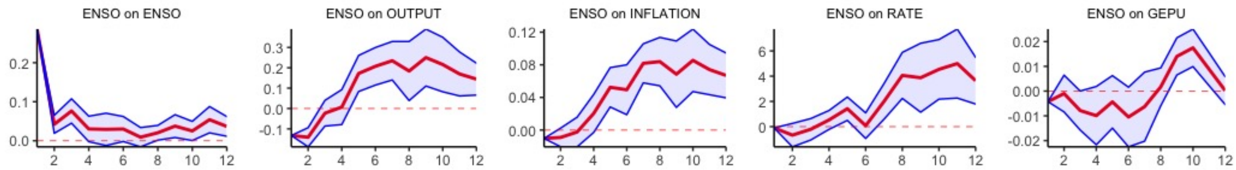
To investigate the dynamic responses from the endogenous variables, the corresponding linear impulse response functions (IRF) relating to shocks to ENSO (Figure 5), output (Figure 6), CPI (Figure 7), interest rate (Figure 8) and EPU (9) are provided. The plot includes the 90% confidence band.

Shock to ENSO

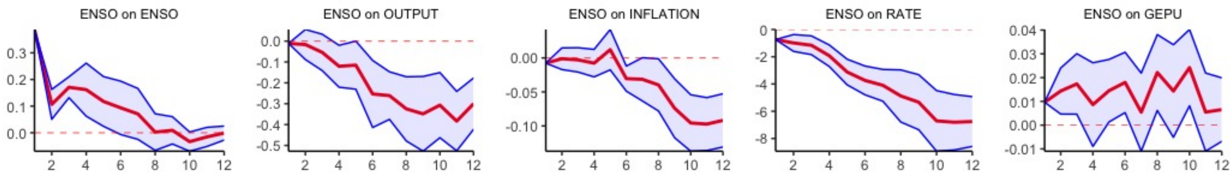
A shock to weather (ESOI) corresponds with an increase in output. Furthermore, the weather shock is inflationary, which results in delayed interest rate response. An ENSO shock results in a decrease (increase) in EPU during an EN (a LN) state.

Figure 5: IRF for ENSO Shock (Baseline Model)

ENSO based on EN Specification



ENSO based on LN Specification

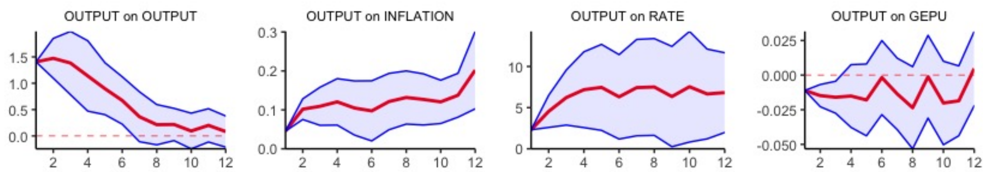


Shock to Output

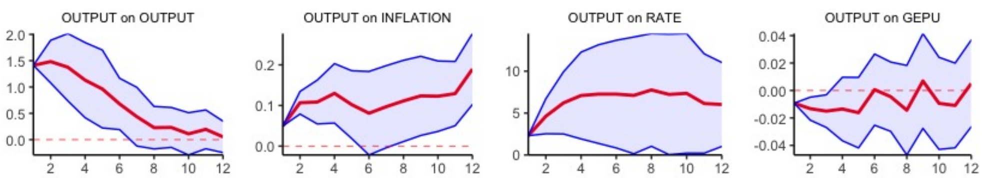
A one-standard deviation shock to output corresponds with higher inflation and interest rate. Global EPU declines slighly in period three, noting the confidence interval is quite wide. The decline in global EPU is consistent with Hailemariam et al. (2019) and Ginn et al. (2021), who finds that an increase in output reduces EPU for the G7 economies and India, respectively.

Figure 6: IRF for Output Shock (Baseline Model)

ENSO based on EN Specification



ENSO based on LN Specification



Shock to Inflation

We observe that a one-standard deviation shock to inflation results in lower output with a four month lag, with an increase in the interest rate. An inflationary pressure results in an increase of EPU.

Shock to Interest Rate

The transmission of monetary policy remains equivocal insofar that the 20 economies pursue monetary policy that is not necessarily coordinated, but rather the "collective stance" by major central banks (Ratti and Vespignani, 2016). A one-standard deviation shock to the interest rate results in higher output on impact which turns negative in period 9; a marginal decline of the inflation rate; and an increase in EPU.

Shock to EPU

The IRFs in 9 are consistent with Colombo (2013); an increase in EPU corresponds with lower output, CPI and interest rate.

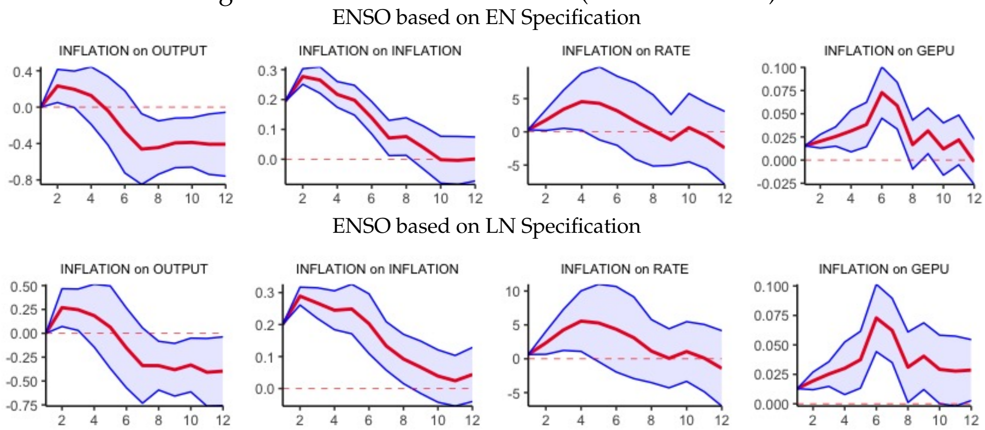


Figure 7: IRF for Inflation Shock (Baseline Model)

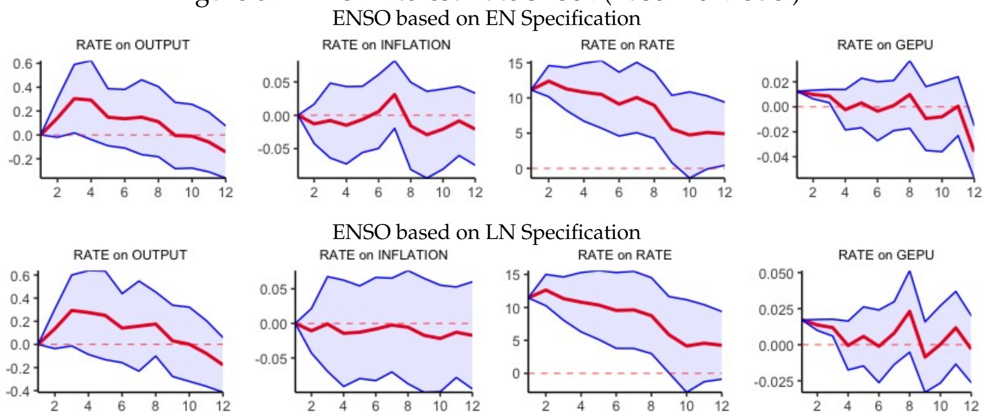


Figure 8: IRF for Interest Rate Shock (Baseline Model)

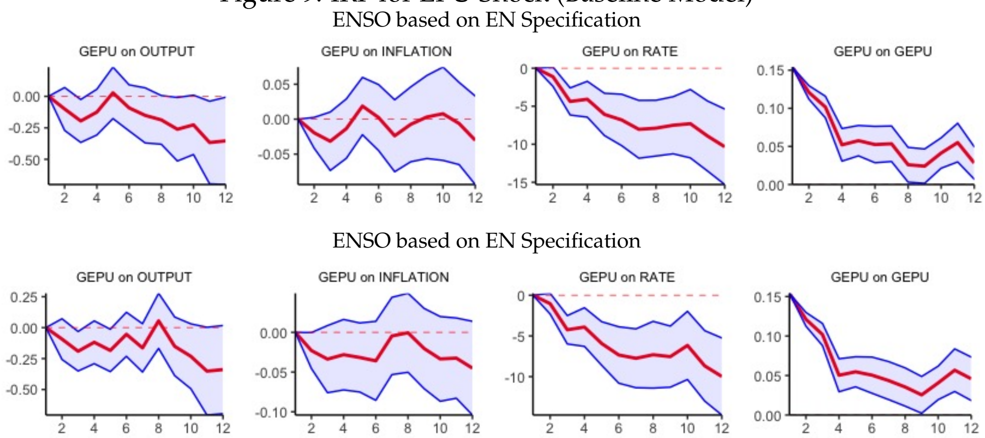


Figure 9: IRF for EPU Shock (Baseline Model)

4.2 Non-Linear Model

Considering weather oscillates via an El Nino and a La Nina periods, the extended model is estimated using a VAR-LP model using a non-linear regime-switching framework to critically examine whether the effects of ENSO weather patterns are state-dependent on economic conditions.

This allows us to test whether a ENSO weather patterns can create an asymmetry (add references). To test this hypothesis, we specify the prediction of y_{t+h} to differ according to an El Nino ("EN") and La Nina ("LN") state when an ENSO weather anomaly shock ($shock_t$) hits. That is, y_t is estimated that includes a smooth transition function $F(\zeta_t)$ that represents the state of the economy:

$$F(\zeta_t) = \frac{\exp(-\gamma\zeta_t)}{1 + \exp(-\gamma\zeta_t)} \tag{9}$$

where ζ_t is a standardized transition variable and γ controls the degree of smoothness of the transition between states. The model has the following functional form:

$$y_{t+h} = trend_t + F(\zeta_{t-1})(\alpha_{h,EN} + \phi_{h,EN}(L)x_{t-1} + \beta_{h,EN} shock_t) + (1 - F(\zeta_{t-1}))(\alpha_{h,LN} + \phi_{h,LN}(L)x_{t-1} + \beta_{h,LN} shock_t) + \epsilon_{t+h} \quad (10)$$

where y_{t+h} is projected on the space generated by a set of control variables (x_{t-1}) defined by the endogenous variables (at lag one). The coefficient $\beta_{h,EN}$ ($\beta_{h,LN}$) corresponds with the estimated impact of climate shock in an EN (a LN) state. Following Auerbach and Gorodnichenko (2012), the transition function is dated $t-1$ to avoid contemporaneous feedback from policy actions with regard to the state of the economy (i.e., $F(\zeta_{t-1})$). We set γ is to 5. The transition variable (ζ_t) is taken as the deviation of the ENSO cycle from a smooth trend.[16]

The IRFs for the non-linear model relating to an ENSO shock are presented in Figure 10. The IRFs indicate the importance of how a ENSO weather affects economic conditions based on the state of the climate.

The transition function for the non-linear model is presented in Figure 11, which plots the evolution of the transition variable $F(z_t)$ along the ENSO climate conditions. By construction, a high (low) value of the transition variable corresponds to an El Nino (a La Nina) period.

Figure 10: IRF for ENSO Shock (Baseline Model)

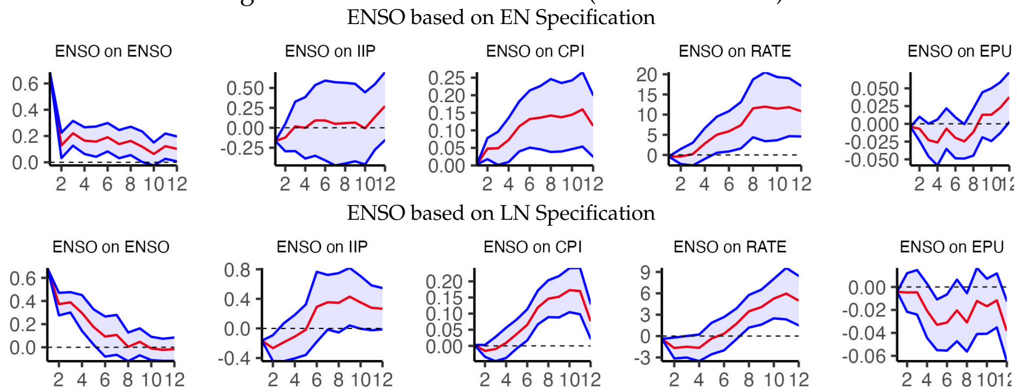


Figure 10 indicates a delayed response of an ENSO shock on economic conditions. The impact of a LN (an EN) shock is marginal (increases) in output, conditional that the system enters into the climate state.

The empirical evidence from the non-linear model (Figure 10) relating to an ENSO shock is no longer consistent with the linear model (Figure 5), insofar that the linear model lacks proper specification along two dimensions.

Firstly, (e.g., Brunner, 2002 and Cashin et al., 2017) analyze the partial effects of an El Nino (a La Nina) shock by "shutting off" the La Nina (El Nino) in their specification. Second, the contribution of an ENSO shock can have lagged effects. We conjecture that the GVARLP methodology fills in both of these gaps, such that an ENSO shock cast in the GVARLP model allows for a more robust framework to estimate the economic system to not necessarily remain static within one state of ENSO (EN or LN) conditional that the system has entered into that state. Overall, our model facilitates a way to capture the full data generating process of how the changing ENSO states affect global economic conditions. Incorporating the effects of climate while integrating an endogenous treatment of commodity prices on a global scale is of critical importance to further inform our understanding of the consequential effects of changing climate *ex post*, an area of paramount importance, considering current assessments of future climate scenarios are shrouded in uncertainty.

4.2.1 Extended Model

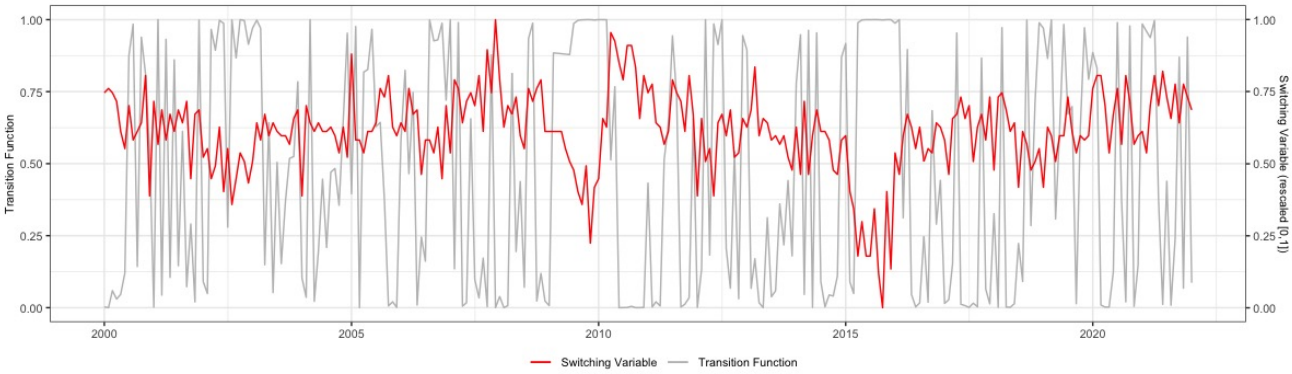
The baseline model is extended to include the international oil and food commodity prices:

$$\boldsymbol{y}_t^T = [ENSO_t^G, \Delta \ln Y_t^G, \Delta \ln P_t^G, \Delta \ln P_{O,t}^G, \Delta \ln P_{F,t}^G, R_t^G, \ln EPU_t^G] \quad (11)$$

The international oil and food price is ordered after CPI in equation (11). Considering the global structure, commodity prices are modeled endogenously, hence there is no information delay where the inclusion of

[16] The trend is based on the Hodrick-Prescott filter with smoothing parameter λ = 129,600 (see e.g. Ravn and Uhlig (2002)), a standard value for data at monthly frequency.

Figure 11: Transition Function for ENSO (Extended Model)



ESOI is used as a switching variable (rescaled [0,1]).

ENSO shocks facilitate an identification to address, in part, why price fluctuations occurred in the first place. Furthermore, we order oil before the food price (e.g., Khan and Ahmed (2011), Khan and Ahmed (2014), Alom et al. (2013) and Ginn et al. (2021)). Commodity prices (in real terms) tend to be endogenous and pro-cyclical to the global business cycle (e.g., Kilian (2009), Kilian and Zhou (2018)). Kilian (2009) distinguishes between demand and supply shocks in the oil price, and finds that increases in the oil price since 2003 are primarily driven by demand. The similar increases in the food price has raised concerns about inflationary pressures. This is finding is also confirmed by Joëts et al. (2017) for corn, soybeans and wheat. This identification is consistent with Alquist and Kilian (2010), who finds that the oil price is determined endogenously and simultaneously.

Impulse Response Function (Extended Model)

The corresponding IRFs are provided for a shock to ENSO (Figure 12), international oil price (Figure 13), international food price (Figure 14) and EPU (Figure 15).[17]

Shock to ENSO

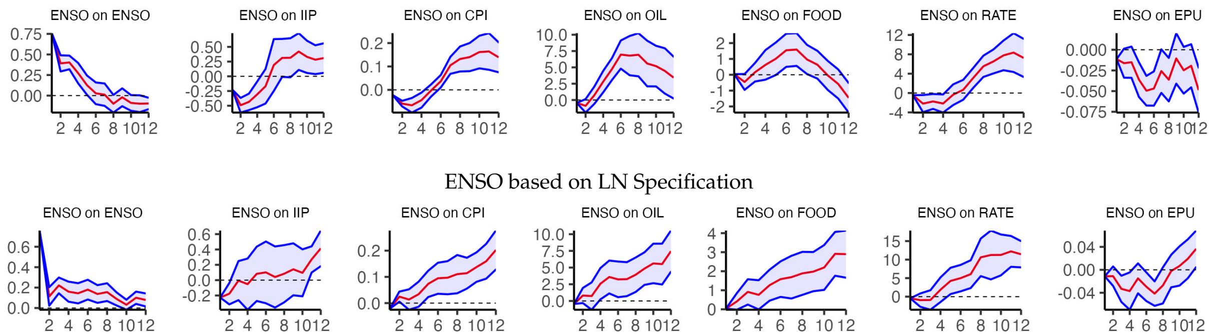
Similar to the baseline model, a shock to ENSO (ESOI) corresponds with an increase in output and is inflationary, which in turn elevates the oil and food price (see Figure 12).

While an ENSO weather shock is inflationary, the effect on impact for oil (food) price is more pronounced in an El Nino (La Nina) state.

The increase in output and prices results in an increase in the interest rate during an EN state. Accordingly, an ENSO shock during an EN state results in a decrease in EPU.[18]

Figure 12: IRF for ENSO Shock (Extended Model)

ENSO based on EN Specification



Shock to International Oil Price

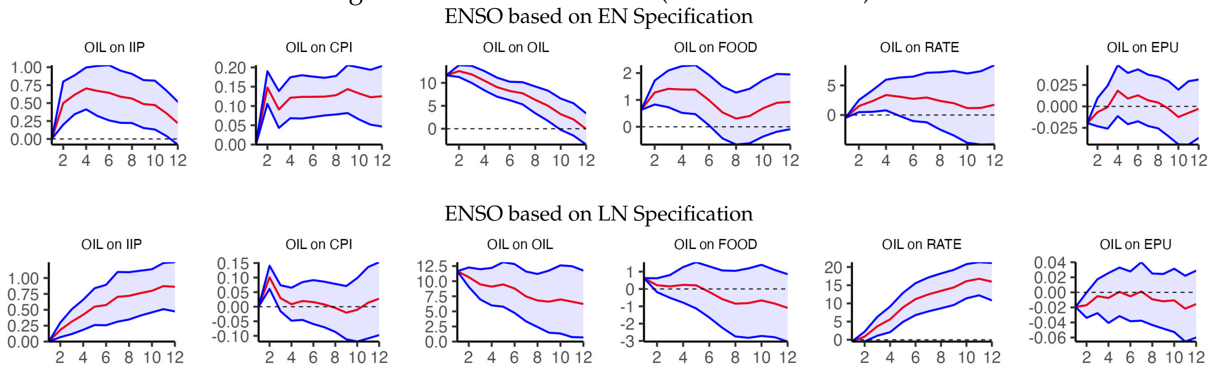
A one-standard deviation shock to the international oil price corresponds with a decrease in EPU (see Figure 13), which is not statistically significant. Hailemariam et al. (2019) find a negative (positive) relationship between oil prices and EPU for a panel of seven OECD (G7) countries. They conjecture the negative relationship

[17] For brevity, the IRFs for the extended model relating to output (Figure 22), CPI (Figure 23) and interest rate (Figure 24) are provided in the Appendix.

[18] These results are consistent with the OLS regression results in Table 2, which shows GEPU increases with higher inflation and lower output and interest rate.

prior to the global financial crisis was due to a "positive effect of aggregate demand on oil prices" which created a "conducive environment for the global economy". Ginn et al. (2021) find that an increase in the oil price results in an increase in EPU for India.

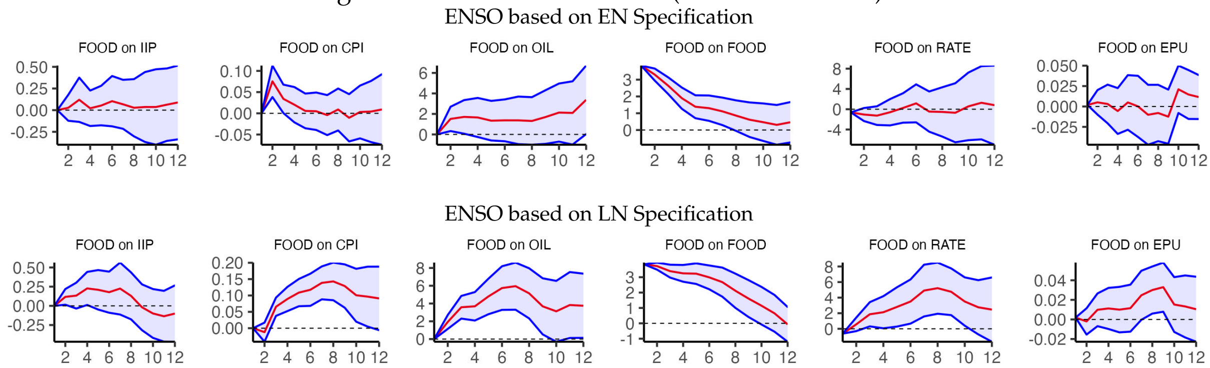
Figure 13: IRF for Oil Shock (Extended Model)



Shock to Food Price

A one-standard deviation shock to the international food price is associated with higher output, inflation (for all price indices) and interest rate (see Figure 14). It turns out that an innovation to the food price can magnify EPU during a LN period.[19] Economically, these results are important if one considers that food prices have been elevated and persistent over the time domain until around 2011, with a subsequent negative decline since (see Figure 2).

Figure 14: IRF for Food Shock (Extended Model)



Shock to EPU

On impact, a one-standard deviation shock to EPU is associated with lower output; lower CPI and oil inflation; higher food inflation; and lower interest rate (see Figure 15). These results are similar to Colombo (2013), who finds an increase in EPU corresponds with lower output, CPI and interest rate.

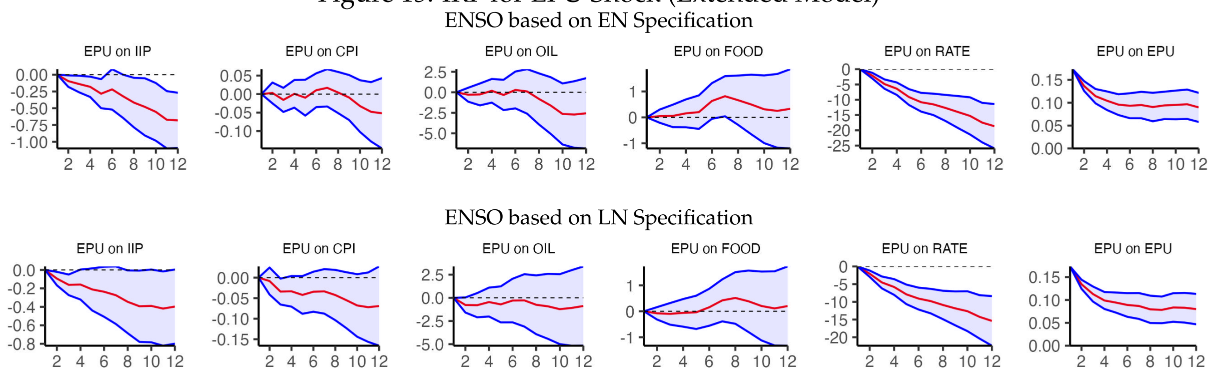
5 Discussion on the Importance of Food Prices

The main results indicate that weather shocks have important and asymmetric effects on economic conditions. A closer inspection of the results show that the food price is a central source of vulnerability on a global scale. This conclusion is drawn from three findings. Higher aggregate and food inflation result in an increase in EPU, which are statistically significant, whereas a positive innovation in oil prices decreases EPU, which is not statistically significant. Furthermore, the findings show that an increase in the international food price augments CPI by 0.15% after six months on impact (see Figure 14).

It is therefore natural to ask, why is the international food price a central source of global vulnerability? Drawing on the literature review by Ginn et al. (2021), this section takes stock of four reasons why the international food price is important.

[19] Bastianin et al. (2018) similarly found that a LN is more harmful than an EN for Colombian coffee, considering the former is associated with lower production which in turn corresponds with a higher price.

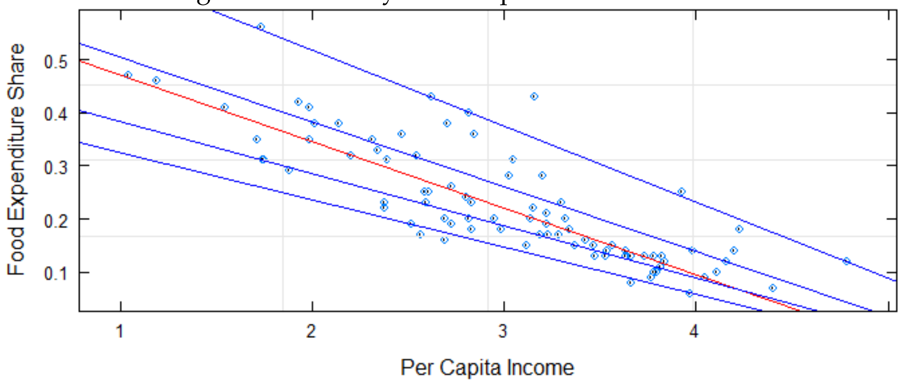
Figure 15: IRF for EPU Shock (Extended Model)



Food Represents a Sizable Portion of Household Expenditures

The share of food expenditures accounts for 48%, 31% and 20% of consumption on average in low-, middle- and high-income countries, respectively (Pourroy et al., 2016).[20] This relationship is known as Engel's law (see Figure 16).[21] As food represents a sizable share of income expenditure and is an inelastic good[22], a sizable price increase in real terms may have an affect, especially for credit-constrained households (e.g., Anand and Prasad (2010), Ginn and Pourroy (2019)).

Figure 16: Country Food Expenditure and Income



Source: US Department of Agriculture Economic Research Service (food expenditure share) and World Bank International Comparison Program database (Income in natural logarithm). The quantile regression shown includes quantiles: 0.05, 0.25, 0.5 (red line), 0.75 and 0.95.

Reaction and efficiency of monetary policy

Over the past few decades, central banks have focused on price stability as one of, if not the the most important, objectives of monetary policy, a framework described as inflation targeting.[23] Yet, a common thread is how policy makers should react to rising commodity prices, which can inevitably make, *inter alia*, monetary policy subject to more uncertainty. The initial research in the monetary policy literature (e.g., Aoki (2001), Bodenstein et al. (2008)) argues that volatile price subsets (e.g., oil and food prices) be stripped away from the objective relating to price stabilization for central banks to the extent that Goodfriend (2007) describes as part of a "consensus model".

The recent literature has reversed course, where the point of departure hinges on the degree of incomplete markets, country-specific characteristics and considering that food prices have been elevated and not necessarily mean-reverting. Recent publications such as Anand et al. (2015), Catão and Chang (2015), Pourroy et al. (2016), Ginn and Pourroy (2019) and Ginn and Pourroy (2020b) find that central banks do not overlook food price inflation, a result in line with central bank management in practice (Hammond, 2012). Food prices can propagate inflation through its effects on inflation expectations (e.g., Walsh (2011), Ginn and Pourroy (2020b)) as a second-round feature on non-food prices.

[20] Low-income, middle-income and high-income countries represent those with real per capita income less than 15 percent, between 15 and 45 percent, and greater than 45 percent of the U.S. level, respectively.

[21] Engel's law is an empirical regularity, or "stylized fact", named after the statistician Ernst Engel (Engel, 1857).

[22] The USDA (International Food Patterns) estimates the elasticity of food to be less than one for all countries.

[23] See Hammond (2012) for a presentation of inflation targeting central banks practices.

Impact on public finance

Rising prices can raise the stakes for fiscal policy-makers confronting ways of alleviating poverty, ensuring food security and maintaining macroeconomic stability. Food inflation may trigger endogenous fiscal policy vis-à-vis a demand driven food price subsidy (Ginn and Pourroy, 2019), which are prevalent, especially in low and middle income countries. Based on a DSGE using Bayesian methods, Ginn and Pourroy (2020a) demonstrate that while monetary and fiscal policy may be viewed as achieving a shared policy goal of price stabilization, the interaction of the two policies can be considered a strategic substitute.

Institutional consequences

Bellemare (2015) shows that food price spikes are correlated with civil unrest. Arezki and Bruckner (2011) find that "during times of international food price increases political institutions in Low Income Countries significantly deteriorated". Gouel (2014) argues that government stabilization policies may be considered as a second-best intervention in the absence of insurance and futures markets.

6 Conclusion

This paper analyzes the global transmission of weather, the oil price and food price as they relate to economic conditions. This paper employs a GVARLP framework, which is estimated using a rich and extensive monthly data set from 1999:01 to 2022:03 relating to twenty-two economies representing 80.2% of global output (based on IMF data for 2021).

This paper contributes to a narrow literature on the "new climate economy" (Dell et al., 2014) in two ways. First, this paper exploits the global estimation framework vis-à-vis the GVARLP to investigate the global dimensions of climate patterns and commodity shocks.

Second, this research documents the presence of international commodity price heterogeneity on EPU. A shock to the international oil (food) price leads to negative (positive) reaction of EPU. The results have rather nuanced implications for policy with regard to an international disturbance that in turn perturbates global economic uncertainty. Accordingly, we find that the food price is source of vulnerability on a global scale, underscoring the importance of global food price stability.

The results from this research have both immediate and long-term policy implications regarding the adaptation to climate changes. A starting point for short-term policy is to establish sources of vulnerability that could create economic risks. The findings from this paper serve to do just that in a global structure by analyzing the propagation mechanisms through which climate shocks influence economic conditions. These insights are of paramount importance to central bank policies designed to understand sources of price changes to stabilize food and aggregate prices, *inter alia*. Similarly fiscal policy is subject to endogenous policy responses to smooth household consumption via food subsidy program.

Over the longer term, policy makers should address the adaptation with regard to climate change. Policy needs to address changes to the social and economic systems from multiple fronts. The central bank must craft an appropriate policy response that monitors and addresses sectoral price developments as they relate to the changing business cycle and the effects of climate change. This is of growing importance as climate change is expected to increase the frequency and intensity of weather patterns (e.g., Timmermann et al. (1999), Chen et al. (2001), An and Wang (2000)). The impact of climate change may influence the central bank's interest rate, which can in turn influence the stock market and investment decisions. Overlooking the effects of changing weather patterns has on future inflation could potentially move inflation away from central bank's target, thereby weakening central bank's monetary anchoring. Similarly, a weather shock that results in higher food prices may create a source of vulnerability with regards to a combination of debt and taxes needed to finance food subsidies.

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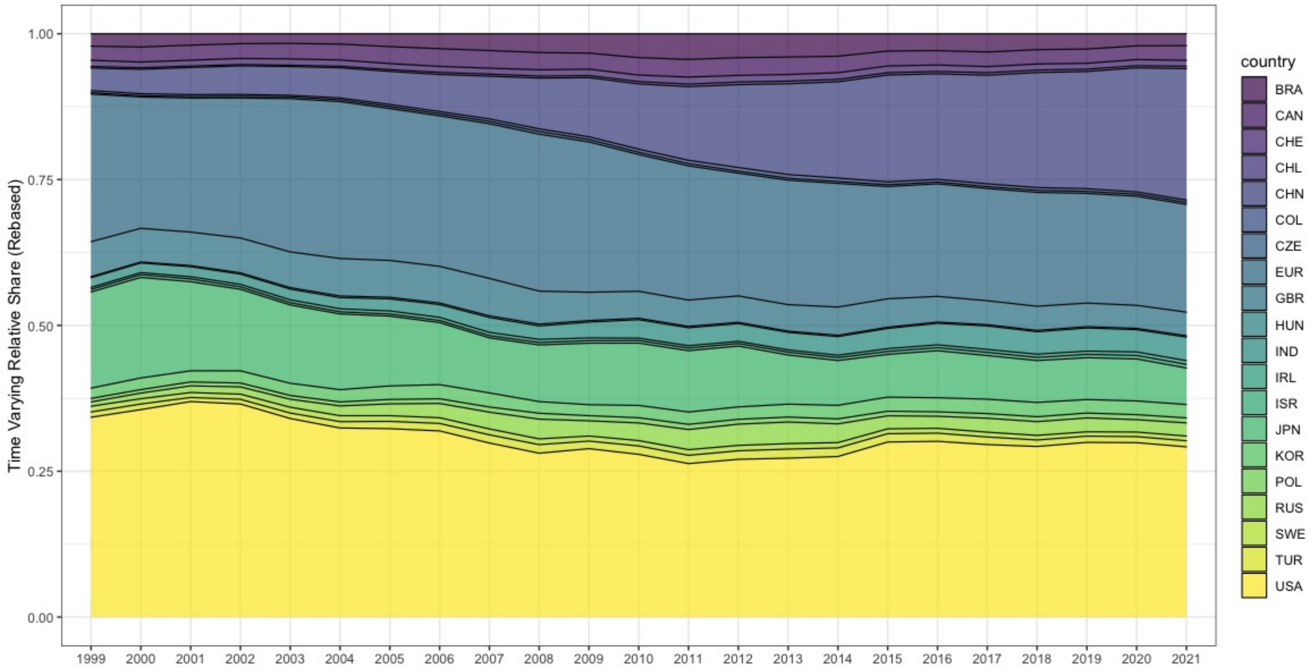
8 Appendix

8.1 GDP Weighted Global Aggregator

Figure 17: Time Varying GDP Weighted Index



Source: IMF based on select economic regions (captures 80.2% global output for 2021).

8.2 Additional IRFs: Baseline Non-Linear Model

The IRFs relating to shocks to output, inflation and the interest rate are provided below:

Figure 18: IRF for Output Shock (Baseline Model)

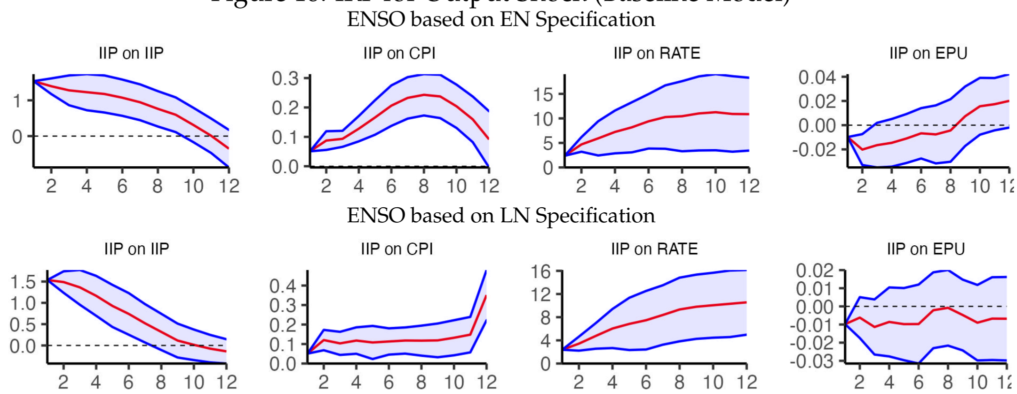
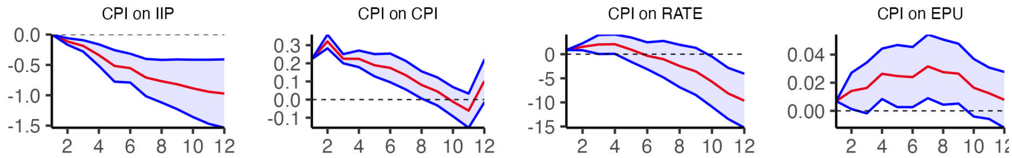


Figure 19: IRF for Inflation Shock (Baseline Model)

ENSO based on EN Specification



ENSO based on LN Specification

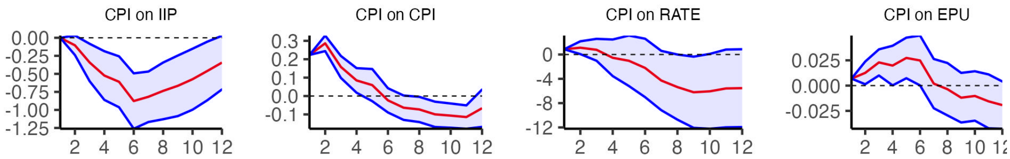
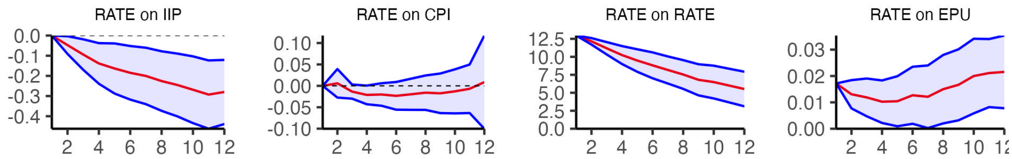


Figure 20: IRF for Rate Shock (Baseline Model)

ENSO based on EN Specification



ENSO based on LN Specification

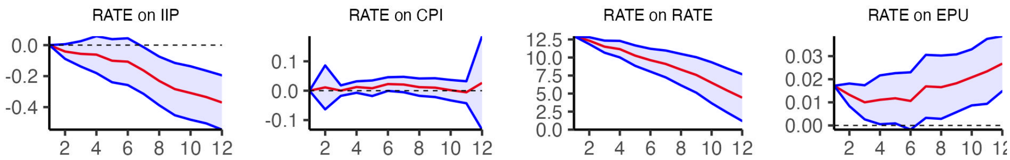
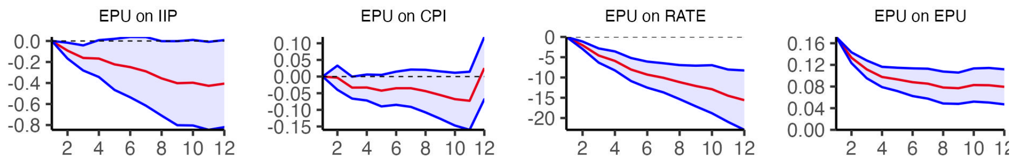
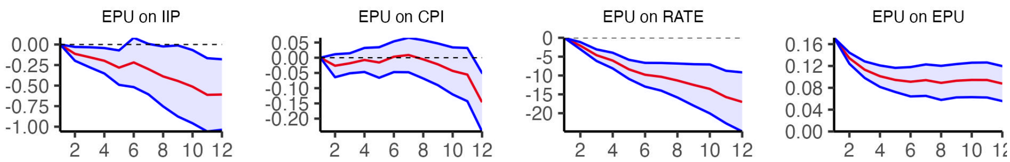


Figure 21: IRF for EPU Shock (Baseline Model)

ENSO based on EN Specification



ENSO based on LN Specification



8.3 Additional IRFs: Extended Non-Linear Model

The IRFs relating to shocks to output, inflation and the interest rate are provided below:

Figure 22: IRF for Output Shock (Extended Model)

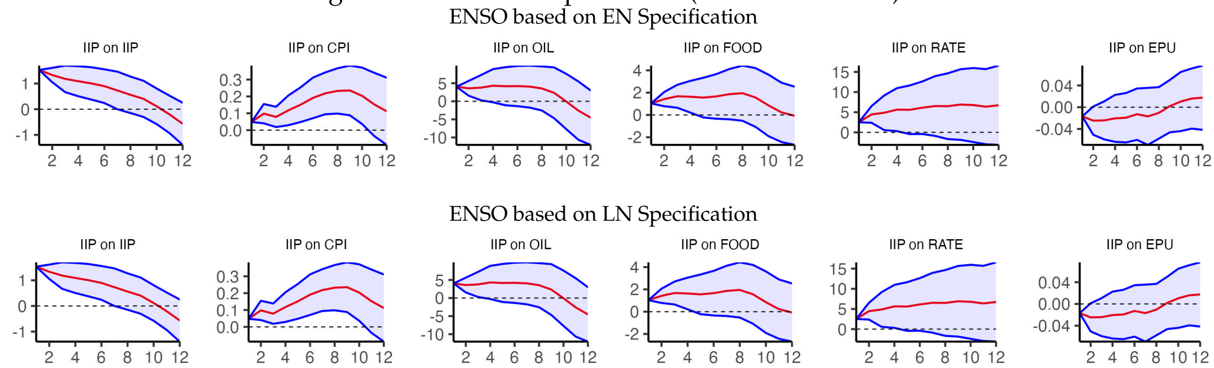


Figure 23: IRF for Inflation Shock (Extended Model)

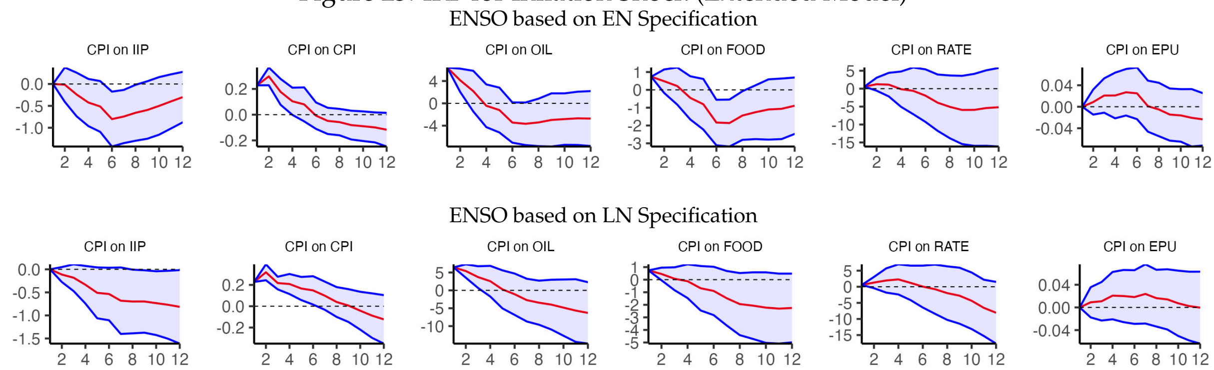


Figure 24: IRF for Rate Shock (Extended Model)