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# Climate pattern effects on global economic conditions<sup>☆</sup>

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## ABSTRACT

This study investigates how El Niño–Southern Oscillation (ENSO) climate patterns affect global economic conditions. Prior research suggests that ENSO phases, particularly El Niño, influence economic outcomes, but with limited consensus on their broader macroeconomic impacts. Using a novel monthly dataset from 20 economies, covering 80% of global output from 1999 to 2022, we employ a global augmented vector autoregression with local projections (GAVARLP) model. The empirical findings suggest that El Niño boosts output with minimal inflationary effects, reducing global economic policy uncertainty, while La Niña raises food inflation, which can amplify aggregate inflation as a “second-round” effect, amplifying uncertainty. These findings shed light on the transmission channels of climate shocks and highlight the significant role of ENSO in shaping global economic conditions, emphasizing why climate shocks should be a concern for policy makers.

## 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). According to NGFS (2021), “[c]limate change is one of the most significant structural force shaping the global economy”. Accordingly, global climate is changing, and there is growing concern it increases the frequency and intensity of weather patterns (e.g., Timmermann et al., 1999; Chen et al., 2001; An and Wang, 2000). Climate change poses serious threats to the core fabrics of the ecological, social and economic systems, yet the impact of changing climate is shrouded in uncertainty. Central to this concern is the effect on economic stability.

However, interest in this issue has been renewed by the Intergovernmental Panel on Climate Change (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).

Our paper focuses on the global effects of an extreme climate phenomenon that causes extreme weather events on a global scale. We consider the anomalies of the warm and cold phases of ENSO (El Niño Southern Oscillation). ENSO describes a climatic pattern that recurs roughly every five years, linked to atmospheric pressure and ocean current cycles, which cause variations in the surface temperature of the eastern tropical Pacific Ocean. This phenomenon redistributes heat and cold waves across the planet. Over the last few decades, this phenomenon has been at the root of strong climatic variability, leading to sharp fluctuations in temperature and a greater frequency of droughts, precipitation and heat waves, as well as abnormally long summers or winters in various regions. In addition, the warm (El Niño) and cold (La Niña) pressure phases of the ENSO phenomenon have been characterized by higher intensities and increasingly shorter frequencies of occurrence.

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We propose a new analytical framework to study the effect of ENSO on global economic activity. This allows us to distinguish between an El Niño and a La Niña climate state. The sensitivity of an economy to natural disasters is not necessarily the same in an El Niño or La Niña phenomenon, because the consequences on the economy of low and high temperatures are not identical. Indeed, an El Niño phenomenon results in severe drought, with losses to infrastructure and the productive capacity of economies far greater than those seen during the floods that accompany La Niña episodes. Moreover, El Niño and La Niña have different amplitudes and different effects in terms of persistence on global activity.

We explore the global dimensions of changing weather patterns overlapping with four 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 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. Ginn (2023b) finds that global commodities (energy, agriculture and metals and minerals) are endogenous to the global business cycle, and that a shock on agriculture inflation has the highest impact on global aggregate inflation.

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 focused on understanding the influence of oil prices (e.g., Kang and Ratti, 2013b; Antonakakis et al., 2014; Hailemariam et al., 2019; Dufrénot et al., 2024) and economic policy uncertainty (EPU), a measure developed by Baker et al. (2016) as an indicator of economic uncertainty. Ginn et al. (2023) 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-investment (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.

The third strand relates to only a handful of papers to address the transmission that ENSO related shocks has on economic conditions (Brunner, 2002; Cashin et al., 2017; De Winne and Peersman, 2018; Peersman, 2018 and Ginn, 2024b). Brunner (2002) finds that El Niño 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. Ginn (2024b) finds that an ENSO shock has a delayed and oscillatory effect on equity returns, with the most significant impact being positive (negative) during an El Niño (a La Niña) phase. These results align with the general findings that an El Niño effect can stimulate economic conditions (e.g., Brunner, 2002; Cashin et al., 2017 and Dufrénot et al., 2021). 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. Morana and Sbrana (2019) associate ENSO

cycle and cat bonds risk, and find that climate change risk might not yet have been properly incorporated in cat bond multiples.

The fourth strand is based on global integration. Using a sample of 63 countries, Kose et al. (2003) provides evidence for a world business cycle. Monfort et al. (2003) and Ratti and Vespignani (2016) show that the G7 and G5 economies exhibit strong comovement, respectively. Ciccarelli and Mojon (2010) find that inflation in industrialized countries is a global phenomenon.

This paper provides four contributions to the literature on ENSO economic impacts (see Smith and Ubilava, 2017; Cashin et al., 2017; Atems and Sardar, 2021).

As a first contribution, we develop a new dataset using economic indicators for twenty economies representing around 80% of global output.<sup>1</sup> The global dataset creates a framework to analyze whether and to what extent a global ENSO shock can transmit a disturbance on the global factor economy. The impact of ENSO cannot be reduced to one country, but rather relates to global climate patterns, which paves the way to understand how climate affects the global economic conditions. 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).

Second, this paper employs a global augmented vector autoregression with local projections (GAVARLP) framework to assess the transmission of an ENSO shock on economic conditions. While this literature is sparse, most 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; and Mainardi, 2011 on Burkina Faso and Niger). Dufrénot et al. (2021) show that the effects of ENSO have asymmetric effects on inflation of numerous globally traded commodities. This paper extends the research by analyzing how ENSO shocks operate at a global level. In this paper, it is the world business cycle that is central to the empirical analysis, motivated by two points. First, we take the time-varying weighted average of output to derive global market economic conditions, considering that numerous authors find evidence of a world business cycle (e.g., Kose et al., 2003; Monfort et al., 2003; Ciccarelli and Mojon, 2010; Ginn, 2023a; Ginn, 2023b; Ginn, 2024c). Secondly, ENSO cycles are a global phenomena. The impact of an El Niño or La Niña cannot be reduced to one country, but rather has global dimensions. Accordingly, the global level modeling facilitates an approach to test the hypothesis whether changing ENSO phases can influence global economic conditions. The sparse, albeit burgeoning literature on the relationship between ENSO variability and economic conditions is mixed, which has not reached a consensus. Liu et al. (2023) and Callahan and Mankin (2023), suggest a non-linear relationship between ENSO variability and economic losses, with extreme El Niño events playing a dominant role. Additionally, Cai et al. (2023) proposes a link between ENSO variability post-1960 and anthropogenic warming. On the other hand, Brunner (2002), Cashin et al. (2017), Dufrénot et al. (2021), and Ginn (2024b), suggests that El Niño events have stimulative effects on economic conditions. Brunner (2002) finds that an El Niño can stimulate output growth for the G-7

<sup>1</sup> 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, the twenty economies considered in this paper represent 76.7% (80.2%) of global output in nominal (purchasing power parity) GDP, see e.g. <https://www.imf.org/external/datamapper/NGDPD@WEO>. 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).

economies. Cashin et al. (2017) find that while there are heterogeneous effects by economy on output growth, an El Niño (a La Niña) is mainly linked with higher (lower) growth in “larger” economies. Ginn (2024b) finds evidence that an ENSO shock has a near uniform positive (negative) and statistically significant impact on equity returns during an El Niño (a La Niña) phase.

Our model facilitates a way to capture the full data generating process of how the changing ENSO states affect global economic conditions. While the majority of the research on climate change is primarily *ex ante* (Noy, 2009), and mainly on prediction and preparation (Cavallo and Noy, 2009), the main contribution of our study is *ex post*, where we incorporate an ENSO shock transmission channel to the economy.

Third, of the rich literature that considers commodity prices, most papers include the oil price. This paper considers not only the oil price, but also the agriculture price. The global factor model approach further allows an identification such that oil and agriculture 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 states, we explore the global linkages that ENSO 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 (El Niño or La Niña) conditional that the system has entered into that state.

Fourth, the existing literature estimates the influence of a partial ENSO shock in isolation (e.g., Brunner, 2002 and Cashin et al., 2017) to analyze the partial effects of an El Niño (a La Niña) shock by “shutting off” the La Niña (El Niño) in their specification, which is problematic considering there is a delayed reaction of ENSO shocks on climate.<sup>2</sup> The GAVARLP facilitates a framework to cast the entire data via changing ENSO states.

The rest of the paper is structured as follows. Section 2 describes the data. Section 3 discusses the global dimensions of the business cycle considered in the paper. The modeling 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 5 concludes the paper.

## 2. Data

The model is based on 20 economies<sup>3</sup> and includes up to six endogenous global variables: 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.<sup>4</sup> The endogenous variables considered include a weather index; industrial production index<sup>5</sup>; the consumer price index (CPI); the world oil price and food commodity price; the short-term interest rate<sup>6</sup>; and EPU. The data is summarized in Table 1. The

<sup>2</sup> According to NOAA, episodes of El Niño and La Niña occur 9 to 12 months. Dufrénot et al. (2021) find there is a delayed reaction on global commodity prices.

<sup>3</sup> Our choice for selecting the 20 economies is based on maximizing the number of countries based on data availability.

<sup>4</sup> 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 (i.e., 76.7% (80.2%) of global GDP in nominal (purchasing power parity) terms using IMF data) of global output. The sample period also overlaps with the commodity price booms that occurred in 2004 (Radetzki, 2006).

<sup>5</sup> For India, manufacturing production index (FRED mnemonic INDPRI-MNT001IXOBM) is used as opposed to total production index (FRED mnemonic INDPRI-MNT001IXOBM), considering data availability (the correlation between the two is 0.9918 for Jan 2000 to Dec 2018). For China, we use total production excluding construction (FRED mnemonic CHNPRINT001IXPYM). As the production index for China includes missing values, the Kalman smoother using an ARIMA state space representation is used to impute missing values.

exogenous variables includes a global financial crisis (GFC) dummy variable (Hailemariam et al., 2019)<sup>7</sup> and U.S. Infectious Diseases Equity Market Volatility Tracker (Baker et al., 2019).<sup>8</sup> We define an ENSO shock ( $ENSO_t^G$ ) based on ESOI anomalies, which is collected from the National Oceanic and Atmospheric Administration (NOAA).

All endogenous variables are converted to logarithm with the exception of the interest rate and ENSO index. For consistency, output for China and India<sup>9</sup>; 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).

## 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 variable is discussed in turn.

### 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. 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).<sup>10</sup>

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).

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), 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. The SOI itself typically compares the atmospheric pressure difference between Tahiti and Darwin in the Pacific Ocean. However, the ESOI focuses on the equatorial Pacific region, specifically comparing the atmospheric pressure at locations near the equator. A positive ESOI indicates lower atmospheric pressure in the equatorial Pacific, which is associated

<sup>6</sup> 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 (2022)).

<sup>7</sup> The GFC dummy variable is set to 1 between 2007:12 to 2009:06, consistent with the NBER recession dates for the U.S.

<sup>8</sup> 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. U.S. Infectious Diseases Equity Market Volatility Tracker is included as a way to capture the prolific and persistent influence that COVID-19 has had on the economic conditions.

<sup>9</sup> Industrial production for other countries in the sample are already seasonally adjusted.

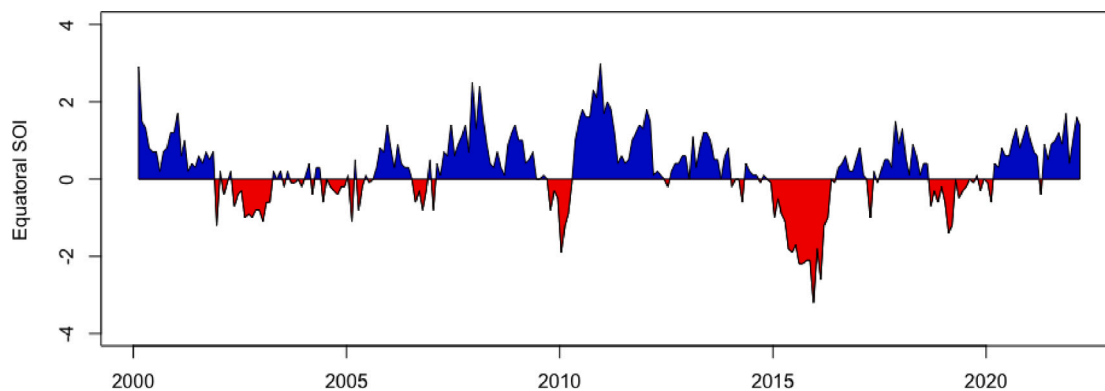
<sup>10</sup> The NOAA considers ENSO as “one of the most important climatic phenomena on Earth”, see <https://www.weather.gov/mhx/ensowhat>.

**Table 1**  
Variable selection.

Item	Symbol	Source	Description
ENSO	$ENSO_t^G$	NOAA	Equatorial Southern Oscillation Index anomalies
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 <sup>a</sup> )	Global EPU
Global Financial Crisis	$GFC_t$	NBER (see <sup>b</sup> )	GFC dummy variable
Infectious Disease	$COVID_t$	FRED	U.S. Infectious Diseases Equity Market Volatility Tracker

<sup>a</sup> <https://www.policyuncertainty.com>.

<sup>b</sup> GFC dummy variable set to 1 between 2007:DEC to 2009:JUN, consistent with the NBER recession dates for the U.S.



**Fig. 1.** Equatorial SOI.

Note: areas shaded red (blue) indicates El Niño (La Niña) conditions. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

with La Niña conditions. Conversely, a negative ESOI suggests higher atmospheric pressure in the equatorial Pacific, which is characteristic of El Niño conditions.

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 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 ENSO data (based on ESOI) is plotted in Fig. 1.

### 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. Fig. 12 in the Appendix shows that the period-to-period movements are quite stable, yet the relationship over a longer period can evolve (see Fig. 2).

### 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.

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”.<sup>11</sup> (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 Fig. 3).<sup>12</sup> (Kilian and Vigfusson, 2017) do not find evidence of a “mechanical relationship” between an increase in the oil price and recessions.

### 3.4. Global EPU

Building on the EPU index by Baker et al. (2016), Davis (2016) constructs a measure of GEPU. GEPU is considered in the empirical analysis. EPU is negatively correlated with the business cycle (e.g., Bloom, 2009 and Baker et al., 2016).

### 3.5. Global variables

Fig. 4 plots the global data which shows the global dataset captures two major turning points. The top-pane shows a sizable decline in

<sup>11</sup> 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.

<sup>12</sup> To illustrate this point, Fig. 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.



Fig. 2. Global aggregates.

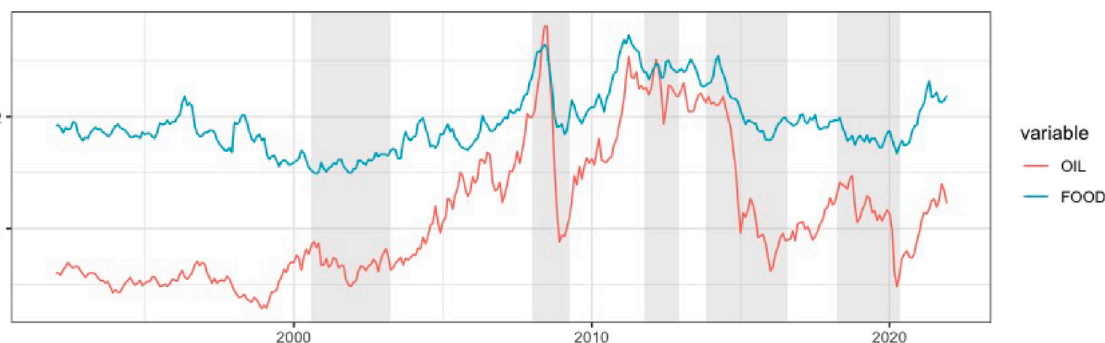


Fig. 3. International oil and food price. Shaded areas indicate OECD recession dates for 35 OECD member and non-member economies as proxy for global recession. Source: FRED (real terms).

output which occurred during the GFC<sup>13</sup> 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.

#### 4. Methodology and results

The vector autoregression model with local projections (VAR-LP), developed by Jordà (2005), is employed to estimate the dynamic responses that a climate shock has on macroeconomic conditions. We estimate the GAVARLP 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.<sup>14</sup> Third, an El Niño and a La Niña are two opposing climate patterns where there can be a lagged effect of each episode.<sup>15</sup>

<sup>13</sup> According to the NBER, the recession dates for the U.S. is between 2007:DEC to 2009:JUN.

<sup>14</sup> The existing research (e.g., Brunner, 2002 and Cashin et al., 2017) analyze the partial effects of an El Niño (a La Niña) shock by “shutting off” the La Niña (El Niño) in their specification.

<sup>15</sup> According to NOAA, episodes of El Niño and La Niña occur 9 to 12 months, see <https://oceanservice.noaa.gov/facts/ninonina.html>.

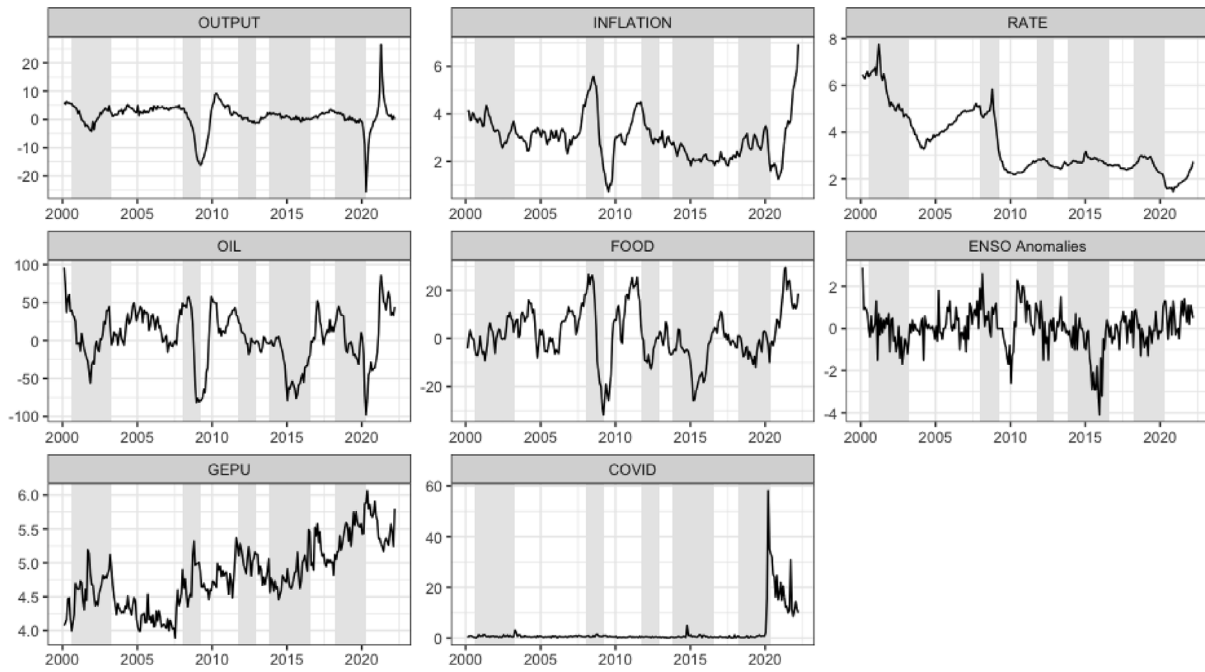


Fig. 4. Global macro indicators.

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.

Considering weather oscillates via an El Niño and a La Niña periods, we estimate 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.

We define an ENSO shock based on ESOI anomalies data (provided in Fig. 4). In contrast to the existing literature, we contend that utilizing the ESOI anomalies data as a measure of an ENSO shock is more suitable than relying solely on ESOI. From an economic standpoint, defining a shock based on ESOI anomalies data proves advantageous for macroeconomic modeling due to three key reasons: its independence from current and past outcome variables; its lack of correlation with other exogenous economic shocks; and it represents unexpected changes in an exogenous variable. The third point calls into question the use of ESOI as a purely exogenous shock, which can be predictably anticipated several months in advance. Consequently, ESOI anomalies, which is defined as the ESOI process that deviates from the long-term average, cannot be reasonably foreseen and thus can be considered truly exogenous.

We therefore specify the prediction of  $y_{t+h}$  to differ according to an El Niño (“EN”) and La Niña (“LN”) state when an ENSO shock ( $shock_t$ ) hits based on the ESOI anomalies data.

Accordingly,  $y_t$  is estimated that includes a smooth transition function  $F(\zeta_t)$  that represents the state of the economy:

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

where  $\zeta_t$  is a standardized transition variable and  $\gamma$  controls the degree of smoothness of the transition between states. The model has the following functional form:

$$y_{t+h} = \delta_1 \tau_t + \delta_2 \tau_t^2 + F(\zeta_{t-1})(\alpha_{h,EN} + \phi_{h,EN}(L)x_{t-1} + \beta_{h,EN} shock_t) + (1 - F(\zeta_{t-1}))(\alpha_{h,LN} + \phi_{h,LN}(L)x_{t-1} + \beta_{h,LN} shock_t) + \epsilon_{t+h} \quad (2)$$

where  $y_{t+h}$  is projected on the space generated by a set of control variables ( $x_{t-1}$ ).<sup>16</sup> The trend term is denoted  $\tau_t$ . The coefficient  $\beta_{h,EN}$  ( $\beta_{h,LN}$ ) corresponds with the estimated impact of climate shock in an

El Niño (a La Niña) 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  $\gamma$  is to 5.1.<sup>17</sup> The transition variable ( $\zeta_t$ ) is taken as the deviation of the ENSO cycle from a smooth trend.<sup>18</sup>

The vector of macroeconomic variables for the baseline model (Model I) includes the following:

$$y_t^T = [\ln EPU_t^G, \Delta \ln Y_t^G, \Delta \ln P_t^G, \Delta \ln P_{O,t}^G, \Delta \ln P_{F,t}^G, R_t^G] \quad (3)$$

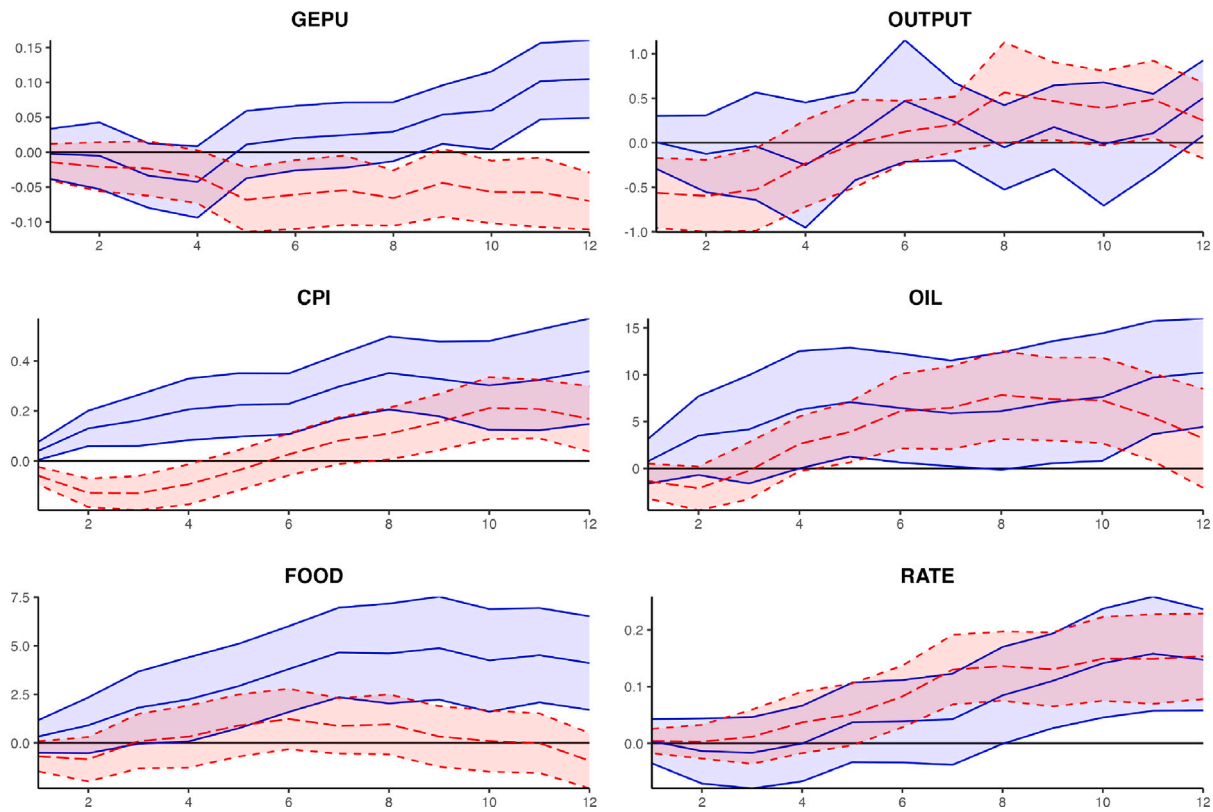
where  $y_t^T$  includes global EPU, output growth, aggregate inflation, oil inflation, food inflation and interest rate. The lag is estimated to include up to 12 lags and evaluated using an information criterion (BIC).

EPU is ordered first in Eq. (3) (Baker et al., 2016), where oil and food inflation is ordered after aggregate inflation. Considering the global structure of the model, commodity prices are modeled endogenously, hence there is no information delay where the inclusion of ENSO shocks facilitate an identification to address, in part, why price fluctuations occurred in the first place. We order oil before the food price (e.g., Khan and Ahmed, 2011; Khan and Ahmed, 2014; Alom et al., 2013). 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; Ginn, 2023b). 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. Montiel Olea et al. (2021) find that oil supply shocks do not materially change oil prices. More generally, Jacks and Stuermer (2020) show that demand shocks dominate supply shocks in driving the commodity prices. This

<sup>16</sup> Consistent with the OLS model, the control variables include the contemporaneous and three lags of global financial crisis indicator and infectious diseases equity volatility tracker is included as a way to capture the prolific and persistent influence that COVID-19 has had on the economic conditions.

<sup>17</sup> This is consistent with the estimated value of  $\gamma$  via LSTAR model (5.1), see Table 2 in Appendix.

<sup>18</sup> The trend is based on the Hodrick–Prescott filter with smoothing parameter  $\lambda = 129,600$  (see e.g. Ravn and Uhlig, 2002), a standard value for data at monthly frequency.



**Fig. 5.** IRF for ENSO shock (Baseline model). El Niño (La Niña) IRFs depicted in red (blue). Model VI is similar to Model I except the model is valued in PPP terms. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

**Table 2**  
LSTAR results.

	Estimate	Std. Error	t value	p value
<b>Low Regime</b>				
$\alpha_1$	-0.3067	0.1642	-1.8683	0.0617
$\phi_1$	-0.0002	0.0003	-0.5928	0.5533
$\phi_{10}$	0.5650	0.0647	8.7353	0.0001***
$\phi_{11}$	0.0651	0.1014	0.6420	0.5209
<b>High Regime</b>				
$\alpha_1$	-0.0684	0.2013	-0.3399	0.7339
$\phi_2$	0.0008	0.0003	2.3390	0.0193*
$\phi_{20}$	-0.3096	0.0796	-3.8881	0.0001***
$\phi_{21}$	0.2896	0.1077	2.6905	0.0071**
<b>Transition Function</b>				
$\gamma$	5.1092	3.0054	1.7000	0.0891*
th	-0.7992	0.2544	-3.1414	0.0017**

Note: \*, \*\* and \*\*\* denote significance at 10%, 5% and 1%, respectively.

identification is consistent with [Alquist and Kilian \(2010\)](#), who finds that the oil price is determined endogenously and simultaneously. The similar increases in the food price has raised concerns about inflationary pressures. This finding is also confirmed by [Joëts et al. \(2017\)](#) for corn, soybeans and wheat. [Falkendal et al. \(2021\)](#) show that local production disruptions have a marginal impact on global prices and supply. They further find that trade restrictions and precautionary purchases could create global food price shocks. [Ginn \(2024a\)](#) finds that while agricultural harvest shocks are important, they exert a comparatively lesser impact than agriculture price shocks. Hence, to maintain a parsimonious model, we do not include the international oil or agriculture production to the VAR.

In this identification setup, we make two departures from the existing literature. First, we deviate from the existing literature such that ENSO is not included as an endogenous variable, whereas other

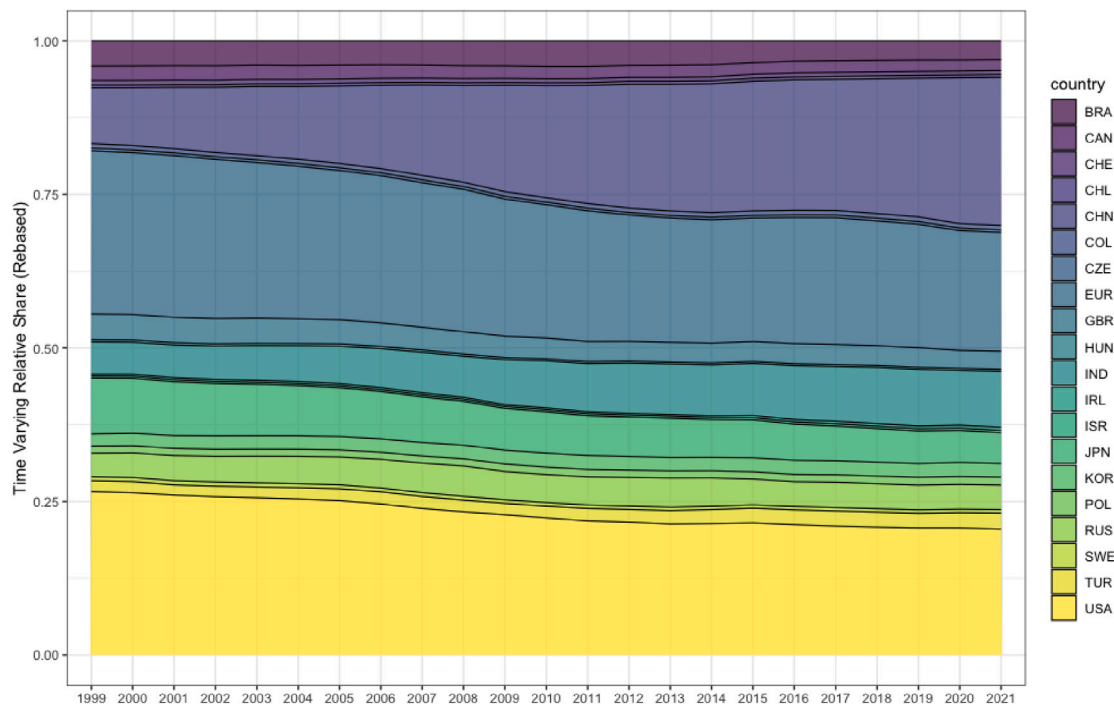
authors treat weather as weakly exogenous, i.e. weather conditions do not contemporaneously affect global macroeconomic conditions ([Brunner, 2002](#); [Cashin et al., 2017](#); [Bastianin et al., 2018](#)). [Brunner \(2002\)](#) estimates a VAR to investigate ENSO and commodity price shocks. [Cashin 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 Niño and a La Niña shock. That is, most papers consider an El Niño shock in isolation.

The second departure is that we add an interest rate, to reflect the “collective stance” by major central banks ([Ratti and Vespignani, 2016](#)). The transmission of monetary policy remains equivocal insofar that policy responses are not necessarily coordinated. Domestic financial conditions can potentially become vulnerable global shocks, which can complicate monetary policy decision making ([Kamin, 2010](#)). While co-movement in domestic inflation rates may be related to cyclical fluctuations in the world economy, as [Woodford \(2007\)](#) shows that globalization does not impair the ability of central banks to control domestic inflation through national monetary policy.

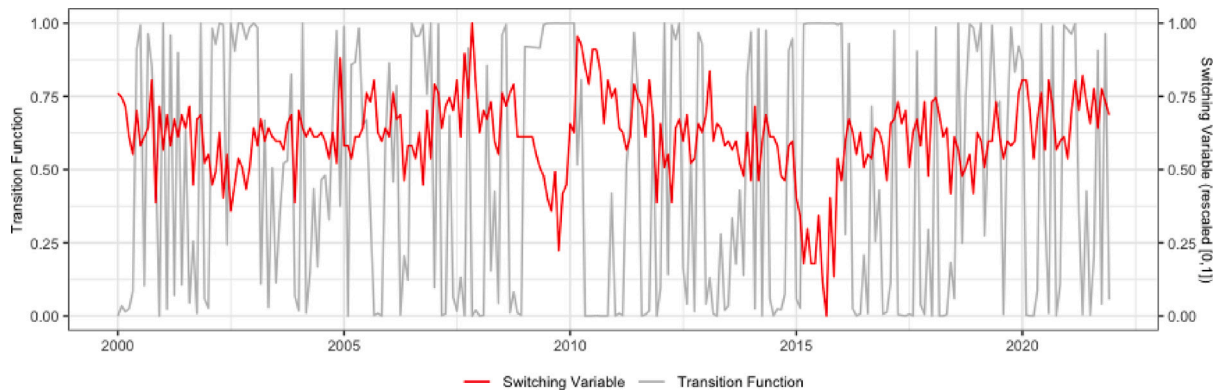
The IRFs for the non-linear model relating to an ENSO shock are presented in [Fig. 5](#). The transition function for the non-linear model is presented in [Fig. 7](#), which plots the evolution of the transition variable  $F(z_t)$  along the ENSO climate conditions. By construction, a high (low) value of the transition variable corresponds to an El Niño (a La Niña) period. The IRFs indicate the importance of how a ENSO weather affects economic conditions based on the state of climate. As there is serial correlation present in the error terms, the Newey–West correction is used for standard errors.

A shock to ENSO results in a delayed increase of output, especially during an El Niño state, which is statistically significant for a number





**Fig. 6.** Time varying GDP (PPP) weighted index. Source: IMF based on select economic regions (captures 76.7% global output for 2021 in PPP terms).



**Fig. 7.** Transition function for ENSO (Baseline model). ESOI anomaly data is used as a switching variable (rescaled [0,1]).

of periods and peaks at period 9.<sup>19</sup> The effect is inflationary, where the impact is more pronounced during a La Niña state (the impact is more punctuated and longer-lasting, which is statistically significant for 9 periods). The delayed increase in the interest rate is statistically significant starting in periods 9. The interest rate is higher during an El Niño period, which coincides with the combination of higher output and inflation.

Fig. 5 indicates a delayed response of an ENSO shock on global EPU, with a similar impact on other variables (as in Model I). Accordingly, a shock to ENSO results in an increase (decrease) in EPU during a La Niña (an El Niño) state. A reason why the EPU response to El Niño and La Niña are different is the following. ENSO changes are associated with precipitation and temperature patterns that can induce floods or

droughts. These extreme phenomena are at the root of economists' differing forecasts of macroeconomic variables, leading to greater uncertainty in economic policy as perceived by economic agents. Moreover, as suggested in another paper by Zhang et al. (2024), climate change leads to higher levels of economic policy uncertainty through, reducing economic growth, widening income disparities, increasing inflationary pressures and unemployment rate.

The findings from the GMM empirical results, summarized in Eq. (5), can help to understand these findings. The GMM model shows that global EPU is increasing (decreasing) in the inflation rate (output growth and interest rate).<sup>20</sup> As output growth is relatively more muted with higher and more persistent inflation in a La Niña state would be

<sup>19</sup> According to NOAA, episodes of El Niño and La Niña occur 9 to 12 months, see <https://oceanservice.noaa.gov/facts/ninonina.html>.

<sup>20</sup> Note that oil and food inflation are excluded from the GMM model. Accordingly, the GMM model is not only parsimonious, but also avoids multi-collinearity among inflation rates.

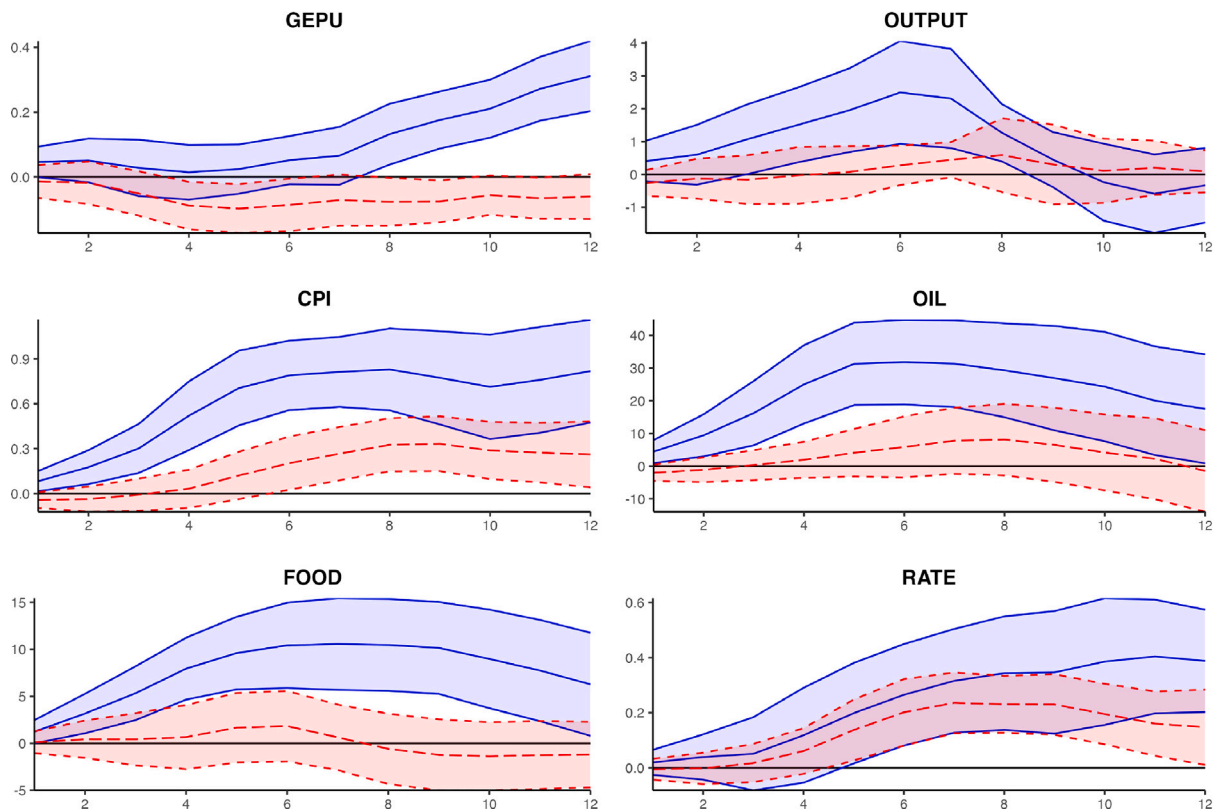


Fig. 8. IRF for ENSO shock (Model II).

El Niño (La Niña) IRFs depicted in red (blue), based on SST as a measure of state dependence. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

consistent with the GMM results. Similarly, an ENSO shock that leads to higher output with relatively less inflation during the El Niño period with a higher interest rate would also be consistent with the GMM results.

A shock to ENSO (based on ESOI anomalies) corresponds with an increase in output and is inflationary, which in turn elevates the oil and food price (see Fig. 5). While an ENSO shock is inflationary, the effect on impact for oil (food) price is more pronounced in an El Niño (La Niña) state. The findings are similar to Dufrénot et al. (2021), such that while both an El Niño and La Niña shock is inflationary, the effect of a La Niña is more pronounced, particularly for food inflation. Higher agriculture inflation can be destabilizing via lower output and higher aggregate inflation (Ginn, 2024b). Ginn (2023b) finds global commodities (energy, agriculture and metals and minerals) are endogenous to the global business cycle, and that a shock on agriculture inflation has the highest impact on global aggregate inflation.

The increase in output and prices results in an increase in the interest rate during an El Niño state. Accordingly, an ENSO shock during an El Niño state results in a decrease in EPU.<sup>21</sup>

#### 4.1. Additional models (Robustness)

For robustness analysis, we further provide six additional models:

<sup>21</sup> These results are consistent with the OLS regression results in Table 3, which shows GEPU increases with higher inflation and lower output and interest rate.

- **Model II:** we estimate Model I where we include the sea surface temperature (SST) as a measure of state dependence.<sup>22</sup> The IRFs are provided in Fig. 8 via Appendix.
- **Model III:** we estimate Model I where we replace the output growth with the output gap based on the HP Filter (Hodrick and Prescott, 1997).<sup>23</sup> The IRFs are provided in Fig. 9.
- **Model IV:** we change the ordering in Model I such that Global EPU is ordered last.<sup>24</sup> The IRFs are provided in Fig. 10.
- **Model V:** we estimate Model I where we change the state dependence from ESOI anomalies using a HP filter to a 12-month centered moving average (MA) of ESOI anomalies. The IRFs are provided in Fig. 11.
- **Model VI:** we estimate Model I where we use GDP based on nominal GDP (see Fig. 12) as opposed to GDP in PPP terms (see Fig. 6). The IRFs are provided in Fig. 13.
- **Model VII:** we estimate Model I where we exclude the USA data from the global variables. The IRFs are provided in Fig. 14 via Appendix.

Overall, all eight models considered consistently demonstrate that there is an asymmetry with the state of the climate as it relates

<sup>22</sup> As the SST is inversely related to SOI, therefore we take the negative value of SST for consistency.

<sup>23</sup> The trend is based on the Hodrick–Prescott filter with smoothing parameter  $\lambda = 129,600$  (see e.g. Ravn and Uhlig, 2002), a standard value for data at monthly frequency.

<sup>24</sup> This rationale follows the approach by Colombo (2013), who orders EPU last to “purge” EPU from the contemporaneous effects on economic conditions.

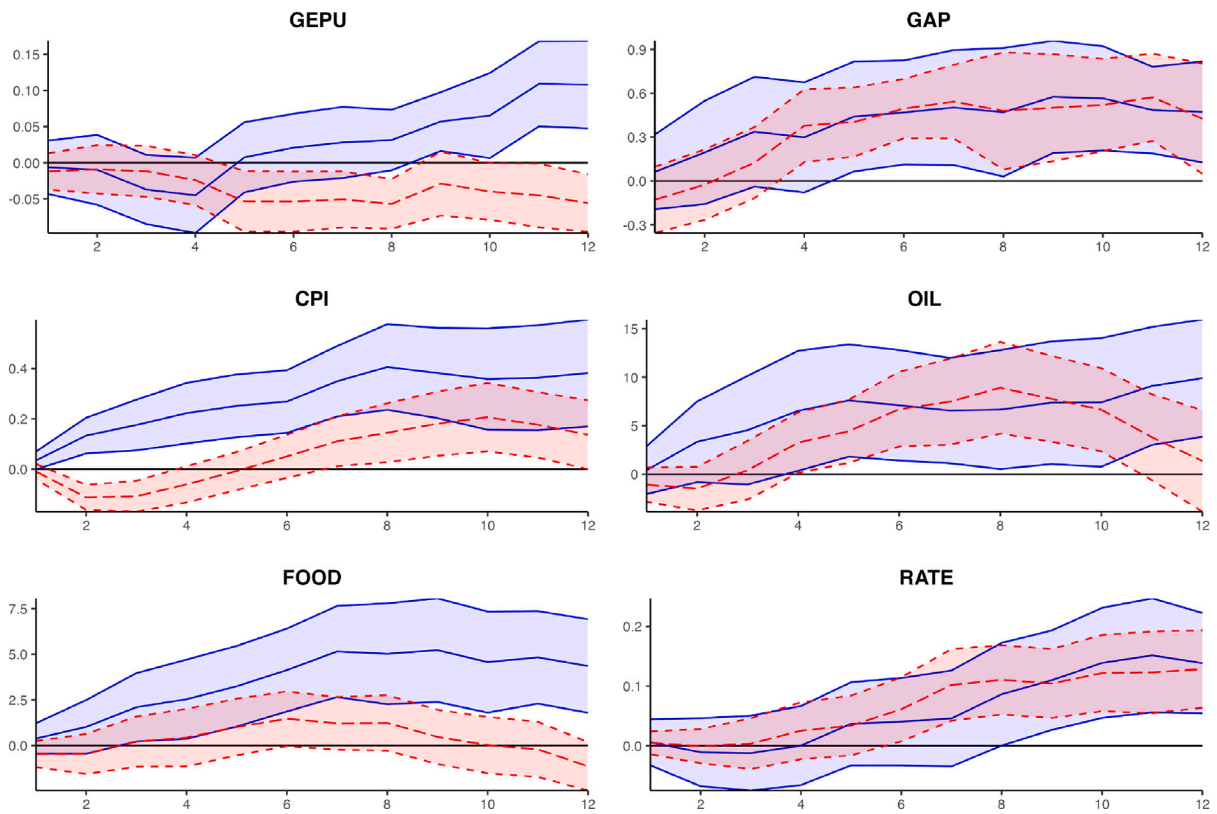


Fig. 9. IRF for ENSO shock (Model III).

El Niño (La Niña) IRFs depicted in red (blue). Model III is similar to Model I except output growth is replaced by the output gap. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

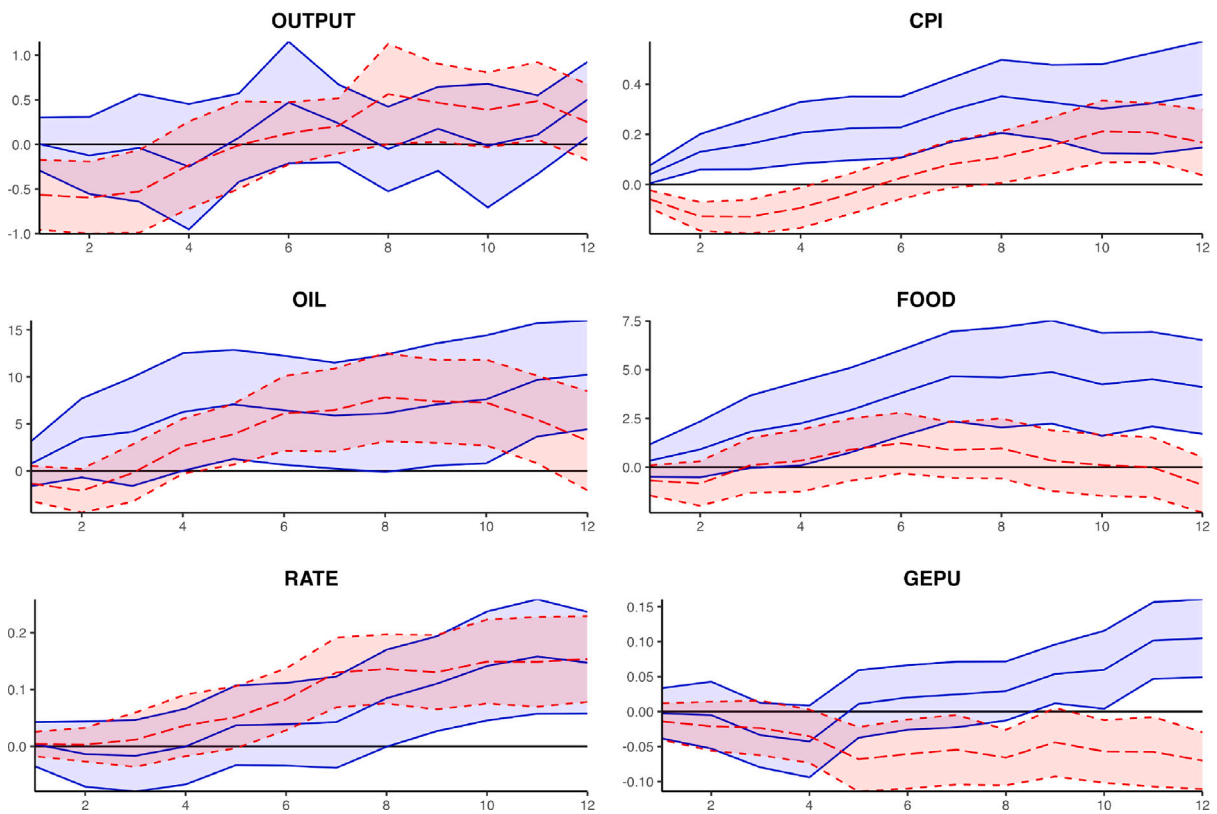


Fig. 10. IRF for ENSO shock (Model IV).

El Niño (La Niña) IRFs depicted in red (blue). Model 4 is based on Model 1 except Global EPU is ordered last. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

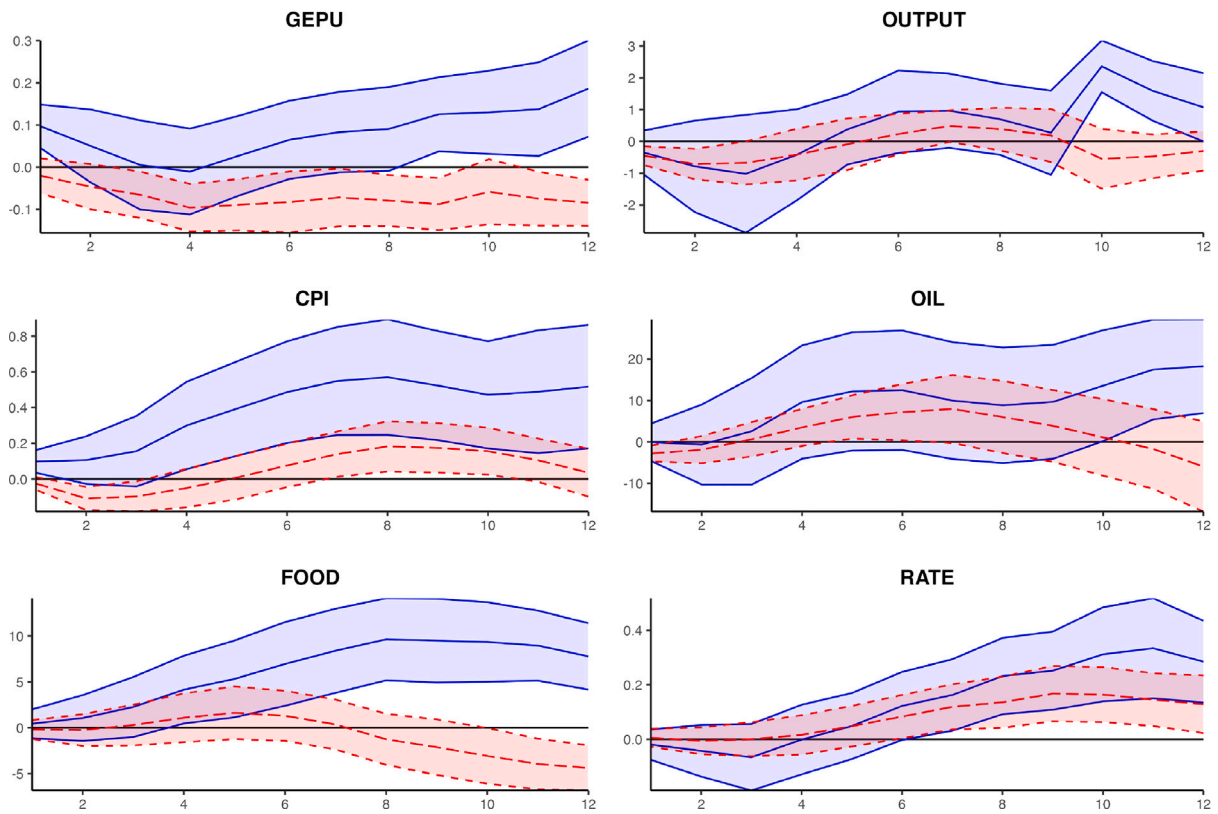


Fig. 11. IRF for ENSO shock (Model V).

El Niño (La Niña) IRFs depicted in red (blue), based on a 3 month centered moving average of ESOI anomalies. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

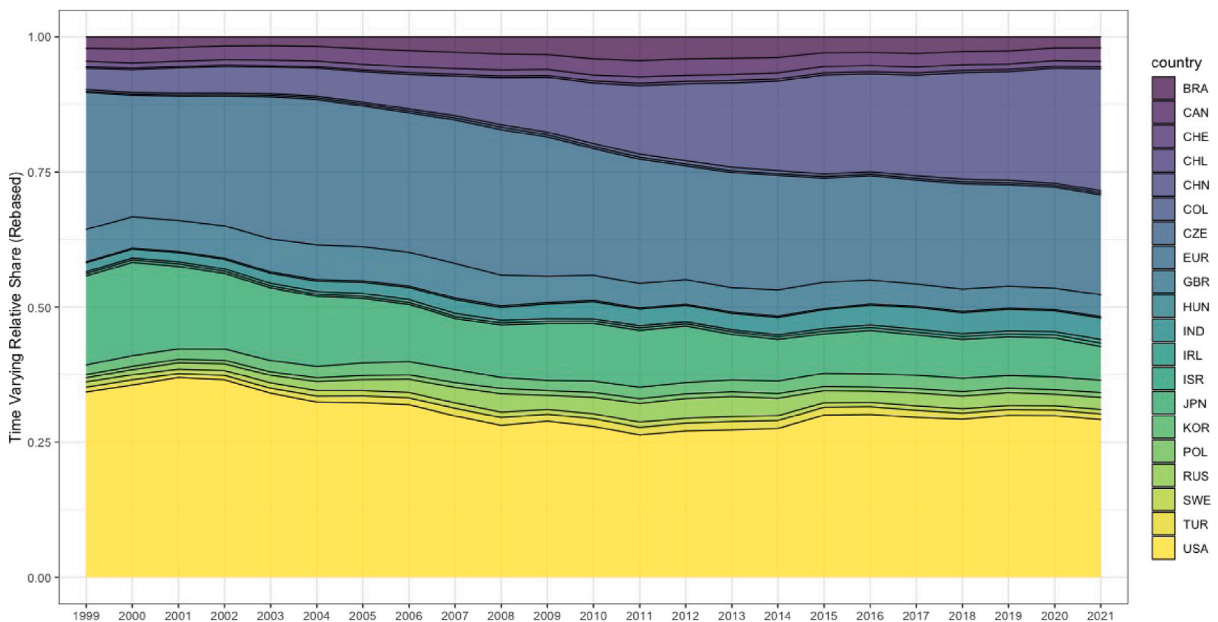


Fig. 12. Time varying nominal GDP weighted index.

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

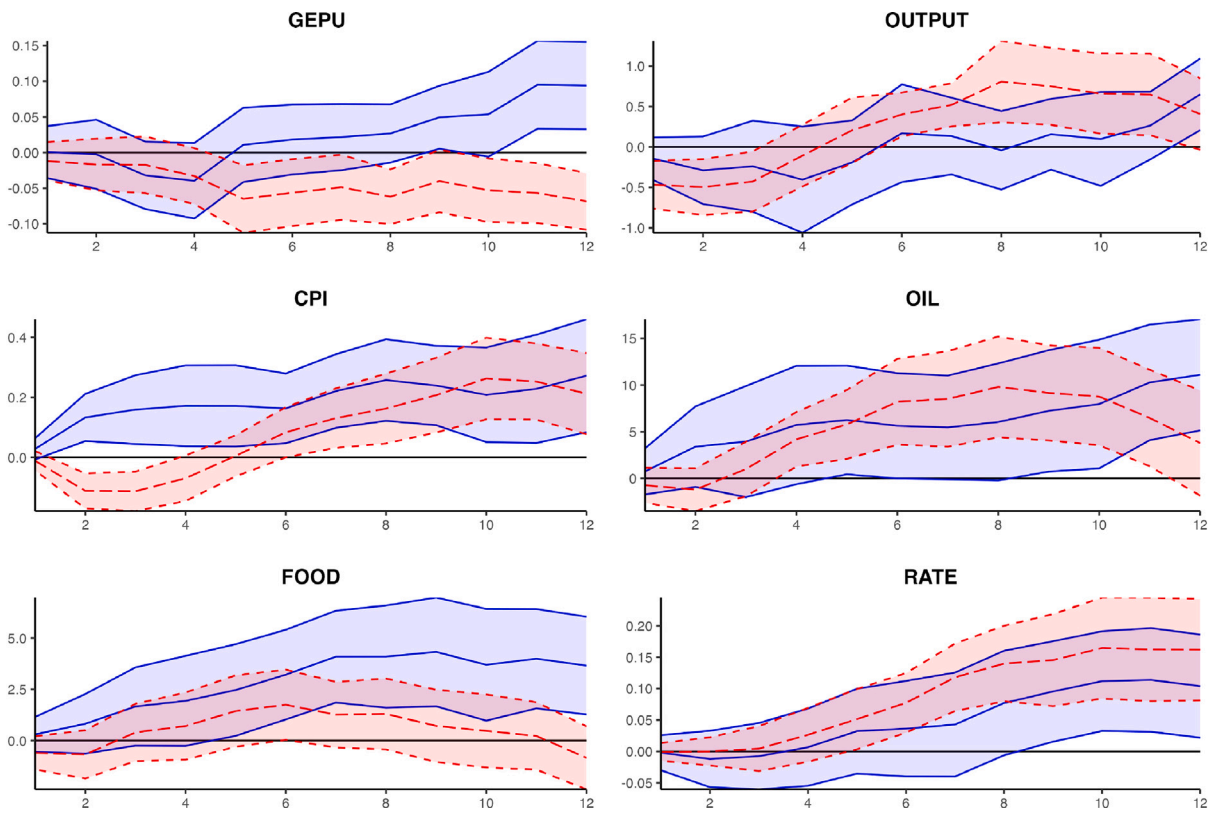


Fig. 13. IRF for ENSO shock (Model VI).

El Niño (La Niña) IRFs depicted in red (blue). Model V is similar to Model I except the model is based on nominal GDP based as opposed to GDP in PPP terms. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

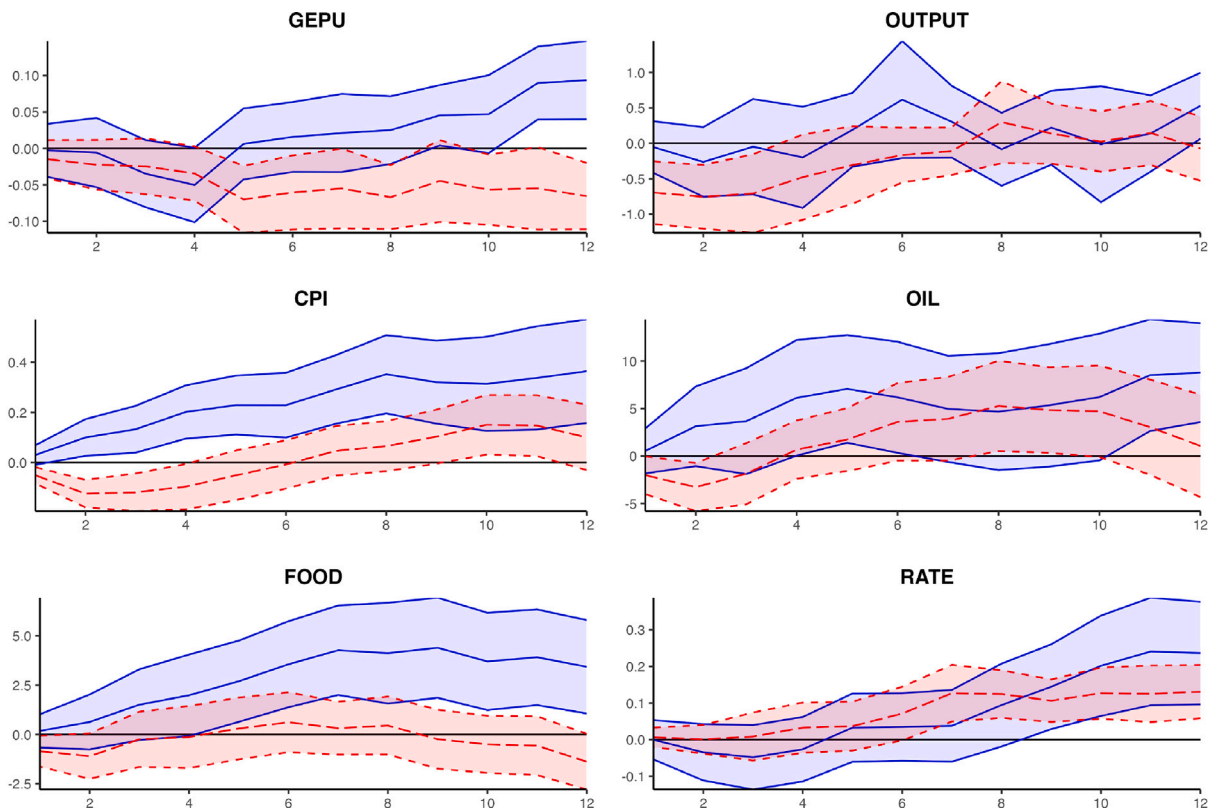


Fig. 14. IRF for ENSO shock (Model VII).

El Niño (La Niña) IRFs depicted in red (blue). Model VII is similar to Model I except the model excludes the USA in the global variables. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

**Table 3**  
GMM regression.

	Estimate	Std. Error	t value	p value
$\alpha$	5.4234	0.18812	28.83	0.0000***
$\beta_Y$	-0.0301	0.01024	-2.94	0.0032***
$\beta_P$	0.0840	0.03958	2.12	0.0337**
$\beta_R$	-0.2362	0.04244	-5.56	0.0000***
$\beta_{COVID}$	0.0147	0.00328	4.47	0.0000***

Note: \*, \*\* and \*\*\* denote significance at 10%, 5% and 1%, respectively.

to economic conditions. An ENSO shock increases (decreases) GEPU during a La Niña (an El Niño) period.

## 5. Conclusion

This paper analyzes the global transmission of ENSO on global economic conditions. This paper employs a GAVARLP framework, which is estimated using a rich and extensive monthly data set from 1999:01 to 2022:03 relating to twenty economies representing around 80% of global output (based on IMF data).

The results from this research have both immediate and long-term policy implications regarding the adaptation to climate changes. Global climate is changing, and there is growing concern it is expected to increase the frequency and intensity of weather events (e.g., Timmermann et al., 1999; Chen et al., 2001; An and Wang, 2000). Climate change poses serious threats to the core fabric of our ecological, social and economic systems, yet the impact of changing climate is shrouded in uncertainty. Central to the concern of climate change is the effect on human life and the environment.

This paper contributes to a narrow literature on the “new climate economy” (Dell et al., 2014). Accordingly, this paper exploits the global estimation framework vis-à-vis the GAVARLP to investigate the global dimensions of climate patterns and commodity shocks. 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. Accordingly, we find that an ENSO shock during a La Niña state elevates food inflation, which can amplify aggregate inflation as a “second-round” effect with ramifications to global 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 climate 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, an ENSO 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.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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## Appendix

### A.1. GDP weighted global aggregator

See Fig. 6.

### A.2. Logistic STAR model

The LSTAR model is used to estimate  $\gamma$  that enters into the logistic function in the local projections model (i.e., Eq. (2)).

$$y_t = (\alpha_1 + \phi_1 \tau_t + \phi_{10} y_{t-1} + \phi_{11} y_{t-2}) F(\zeta_t, \gamma, th) + (\alpha_2 + \phi_2 \tau_t + \phi_{20} y_{t-1} + \phi_{21} y_{t-2})(1 - F(\zeta_t, \gamma, th)) + \epsilon_t \quad (4)$$

where  $F(\zeta_t, \gamma, th)$  is the logistic function. The LSTAR regression results provided in Table 2:

The non-linearity test of full-order LSTAR model against full-order AR model yields an F-value of 3.8832, which corresponds with a  $p$ -value = 0.0209. Thus, we can conclude the ENSO anomalies data, which oscillates depending on the climate phase of El Niño and La Niña, is non-linear.

### A.3. Transition function for ENSO States

See Fig. 7.

### A.4. GMM estimator for GEPU

In this section, we examine the impact of how economic conditions can influence EPU.

There may be an endogeneity issue, considering there is a causal link between EPU and economic conditions to likely be bi-directional. As a conventional ordinary least squares (OLS) model assumes that the explanatory variables are exogenous, this may not hold true in the presence of a feedback loop. We therefore opt to estimating a GMM which allows for the inclusion of lagged control variables, addressing endogeneity concerns by capturing the temporal dimension of the data.

Using our novel dataset defined in Section 3.4, we estimate a regression model based on General Method of Moments (GMM) in parallel to aid in understanding the analytical results of the GAVARLP model. The GMM regression model is formalized as follows:

$$\ln EPU_t = \alpha + \beta^T x_t + B(L)\theta_t + u_t \quad (5)$$

where  $x_t$  is a vector of control variables in the set  $x_t = [\Delta \ln(Y_t^G), \Delta \ln(P_t^G), R_t^G, COVID_t]$ , which includes output growth, aggregate inflation, interest rate and infectious diseases data.<sup>25</sup> The model further includes an intercept ( $\alpha$ ), a vector of lagged control variables ( $\theta_t$ ) and an error term ( $u_t$ ). We set the lag operator (i.e., B(L)) of the control variables to 2.<sup>26</sup> The empirical results are provided in Table 3.

The results suggests that GEPU is associated with lower output growth, higher inflation and lower 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.

<sup>25</sup> Note that oil and food inflation are excluded from the GMM model. Accordingly, the GMM model is not only parsimonious, but also avoids multi-colinearity among inflation rates.

<sup>26</sup> The results are not sensitive to the choice of the lag order of the control variables.

## A.5. IRFs of alternative models

See Figs. 8–14.

## Data availability

Data will be made available on request.

## References

- Alexander, M., Bladé, I., Newman, M., Lanzante, J., Lau, N.-C., Scott, J., 2002. The atmospheric bridge: The influence of ENSO teleconnections on air–sea interaction over the global oceans. *J. Clim.* 15 (16), 2205–2231.
- Alom, F., Ward, B., Hu, B., 2013. Macroeconomic effects of world oil and food price shocks in Asia and Pacific economies: application of SVAR models. *OPEC Energy Rev.* 37 (3), 327–372.
- Alquist, R., Kilian, L., 2010. What do we learn from the price of crude oil futures? *J. Appl. Econometrics* 25 (4), 539–573.
- An, S.-L., Wang, B., 2000. Interdecadal change of the structure of the ENSO mode and its impact on the ENSO frequency. *J. Clim.* 13 (12), 2044–2055.
- Anand, R., Ding, D., Tulin, V., 2014. Food Inflation in India: The Role for Monetary Policy, (no. 14–178), International Monetary Fund.
- Antonakakis, N., Chatziantoniou, I., Filis, G., 2013. Dynamic co-movements of stock market returns, implied volatility and policy uncertainty. *Econom. Lett.* 120 (1), 87–92.
- Antonakakis, N., Chatziantoniou, I., Filis, G., 2014. Dynamic spillovers of oil price shocks and economic policy uncertainty. *Energy Econ.* 44, 433–447.
- Aroui, M., Rault, C., Teulon, F., 2014. Economic policy uncertainty, oil price shocks and GCC stock markets. *Econ. Bull.* 34 (3), 1822–1834.
- Atems, B., Sardar, N., 2021. Exploring asymmetries in the effects of El Niño-Southern Oscillation on US food and agricultural stock prices. *Q. Rev. Econ. Finance* 81, 1–14.
- Auerbach, A.J., Gorodnichenko, Y., 2012. Measuring the output responses to fiscal policy. *Am. Econ. J. Econ. Policy* 4 (2), 1–27.
- Baker, S., Bloom, N., Davis, S., 2016. Measuring economic policy uncertainty. *Q. J. Econ.* 131 (4), 1593–1636.
- Baker, S., Bloom, N., Davis, S.J., Kost, K., 2019. Policy News and Stock Market Volatility. Technical Report, National Bureau of Economic Research.
- Barlow, M., Nigam, S., Berbery, E., 2001. ENSO, Pacific decadal variability, and US summertime precipitation, drought, and stream flow. *J. Clim.* 14 (9), 2105–2128.
- Barnston, A., 2015. Why are there so many ENSO indexes, instead of just one. NOAA Climate. Gov.
- Bastianin, A., Lanza, A., Manera, M., 2018. Economic impacts of El Niño Southern Oscillation: evidence from the Colombian coffee market. *Agricult. Econ.* 49 (5), 623–633.
- Bloom, N., 2009. The impact of uncertainty shocks. *Econometrica* 77 (3), 623–685.
- Bodenstein, M., Erceg, C., Guerrieri, L., 2011. Oil shocks and external adjustment. *J. Int. Econ.* 83 (2), 168–184.
- Brönnimann, S., Xoplaki, E., Casty, C., Pauling, A., Luterbacher, J., 2007. ENSO influence on Europe during the last centuries. *Clim. Dyn.* 28 (2–3), 181–197.
- Brunner, A., 2002. El Niño and world primary commodity prices: warm water or hot air? *Rev. Econ. Stat.* 84 (1), 176–183.
- Burke, M., Hsiang, S.M., Miguel, E., 2015. Global non-linear effect of temperature on economic production. *Nature* 527 (7577), 235–239.
- Caggiano, G., Castelnuovo, E., Fugueres, J.M., 2017. Economic policy uncertainty and unemployment in the United States: A nonlinear approach. *Econom. Lett.* 151, 31–34.
- Caggiano, G., Castelnuovo, E., Groshenny, N., 2014. Uncertainty shocks and unemployment dynamics in US recessions. *J. Monetary Econ.* 67, 78–92.
- Cai, W., Ng, B., Geng, T., Jia, F., Wu, L., Wang, G., Liu, Y., Gan, B., Yang, K., Santoso, A., et al., 2023. Anthropogenic impacts on twentieth-century ENSO variability changes. *Nat. Rev. Earth Environ.* 1–12.
- Callahan, C., Mankin, J., 2023. Persistent effect of El Niño on global economic growth. *Science* 380 (6649), 1064–1069.
- Cashin, P., Mohaddès, K., Raissi, M., 2017. Fair weather or foul? The macroeconomic effects of El Niño. *J. Int. Econ.* 106, 37–54.
- Cavallo, E.A., Noy, I., 2009. The Economics of Natural Disasters: A Survey. Inter-American Development Bank.
- Chen, C.-C., McCarl, B., Adams, R., 2001. Economic implications of potential ENSO frequency and strength shifts. *Clim. Change* 49 (1), 147–159.
- Ciccarelli, M., Mojon, B., 2010. Global inflation. *Rev. Econ. Stat.* 92 (3), 524–535.
- Colombo, V., 2013. Economic policy uncertainty in the US: Does it matter for the Euro area? *Econom. Lett.* 121 (1), 39–42.
- Dai, A., 2013. Increasing drought under global warming in observations and models. *Nature Clim. Change* 3 (1), 52–58.
- Davis, S.J., 2016. An Index of Global Economic Policy Uncertainty. Technical Report, National Bureau of Economic Research.
- De Winne, J., Peersman, G., 2018. Agricultural Price Shocks and Business Cycles-A Global Warning for Advanced Economies. CESifo Working Paper Series.
- DeFries, R., Edenhofer, O., Halliday, A., Heal, G., Lenton, T., Puma, M., Rising, J., Rockström, J., Ruane, A., Schellnhuber, H., 2019. The missing economic risks in assessments of climate change impacts.
- Dell, M., Jones, B.F., Olken, B.A., 2014. What do we learn from the weather? The new climate-economy literature. *J. Econ. Lit.* 52 (3), 740–798.
- Diaz, H., Hoerling, M., Eischeid, J., 2001. ENSO variability, teleconnections and climate change. *Int. J. Climatol. J. Royal Meteorol. Soc.* 21 (15), 1845–1862.
- Dietz, S., Stern, N., 2015. Endogenous growth, convexity of damage and climate risk: how Nordhaus' framework supports deep cuts in carbon emissions. *Econ. J.* 125 (583), 574–620.
- Dufrénot, G., Ginn, W., Pourroy, M., 2021. The effect of ENSO shocks on commodity prices: A multi-time scale approach.
- Dufrénot, G., Ginn, W., Pourroy, M., Sullivan, A., 2024. Does state dependence matter in relation to oil price shocks on global economic conditions? *Stud. Nonlinear Dyn. Econom.*
- Falkendal, T., Otto, C., Schewe, J., Jägermeyr, J., Konar, M., Kumm, M., Watkins, B., Puma, M., 2021. Grain export restrictions during COVID-19 risk food insecurity in many low-and middle-income countries. *Nat. Food* 2 (1), 11–14.
- Gabriel, V., Levine, P., Pearlman, J., Yang, B., 2012. An estimated DSGE model of the Indian economy. In: Chetan Ghat (Ed.), *The Oxford Handbook of the Indian Economy*. Oxford University Press.
- Ginn, W., 2022. Climate disasters and the macroeconomy: Does state-dependence matter? Evidence for the US. *Econ. Disasters Clim. Chang.* 6, 141–161.
- Ginn, W., 2023a. The impact of economic policy uncertainty on stock prices. *Econom. Lett.* 111432.
- Ginn, W., 2023b. World output and commodity price cycles. *Int. Econ. J.* 37, 540–554.
- Ginn, W., 2024a. Agricultural fluctuations and global economic conditions. *Rev. World Econ.* 1–20.
- Ginn, W., 2024b. Does ENSO impact equity returns? Evidence via country & panel regression. *Int. Econ. J.*
- Ginn, W., 2024c. Global supply chain disruptions and financial conditions. *Econom. Lett.* 239, 111739.
- Ginn, W., Kaehler, J., Pourroy, M., 2023. Uncertainty and food prices.
- Ginn, W., Pourroy, M., 2022. The contribution of food subsidy policy to monetary policy in India. *Econ. Model.* 113, 105904.
- Hailemariam, A., Smyth, R., Zhang, X., 2019. Oil prices and economic policy uncertainty: Evidence from a nonparametric panel data model. *Energy Econ.* 83, 40–51.
- Hamilton, J., 1983. Oil and the macroeconomy since World War II. *J. Polit. Econ.* 91 (2), 228–248.
- Hamilton, J., 2008. Oil and the macroeconomy. *The New Palgrave Dictionary of Economics*, vol. 2, Palgrave MacMillan Ltd New York.
- Handley, K., Limao, N., 2015. Trade and investment under policy uncertainty: theory and firm evidence. *Am. Econ. J. Econ. Policy* 7 (4), 189–222.
- Hodrick, R., Prescott, E., 1997. Postwar US business cycles: an empirical investigation. *J. Money Credit Bank.* 1–16.
- Jacks, D., Stuermer, M., 2020. What drives commodity price booms and busts? *Energy Econ.* 85, 104035.
- Joëts, M., Mignon, V., Razafindrabe, T., 2017. Does the volatility of commodity prices reflect macroeconomic uncertainty? *Energy Econ.* 68, 313–326.
- Jordà, Ò., 2005. Estimation and inference of impulse responses by local projections. *Amer. Econ. Rev.* 95 (1), 161–182.
- Kamin, S., 2010. Financial Globalization and Monetary Policy. Technical Report 1002, International Finance Discussion Papers.
- Kang, W., de Gracia, F., Ratti, R., 2017. Oil price shocks, policy uncertainty, and stock returns of oil and gas corporations. *J. Int. Money Finance* 70, 344–359.
- Kang, W., Lee, K., Ratti, R., 2014. Economic policy uncertainty and firm-level investment. *J. Macroecon.* 39, 42–53.
- Kang, W., Ratti, R., 2013a. Oil shocks, policy uncertainty and stock market return. *J. Int. Financ. Mark. Inst. Money* 26, 305–318.
- Kang, W., Ratti, R., 2013b. Structural oil price shocks and policy uncertainty. *Econ. Model.* 35, 314–319.
- Khan, M., Ahmed, A., 2011. Macroeconomic effects of global food and oil price shocks to the Pakistan economy: A structural vector autoregressive (SVAR) analysis. *Pak. Dev. Rev.* 50 (4), 491–511.
- Khan, M., Ahmed, A., 2014. Revisiting the macroeconomic effects of oil and food price shocks to Pakistan economy: A structural vector autoregressive (SVAR) analysis. *OPEC Energy Rev.* 38 (2), 184–215.
- Kilian, L., 2009. Not all oil price shocks are alike: Disentangling demand and supply shocks in the crude oil market. *Amer. Econ. Rev.* 99 (3), 1053–1069.
- Kilian, L., 2014. Oil Price Shocks: Causes and Consequences. Annual Reviews.
- Kilian, L., Vigfusson, R., 2017. The role of oil price shocks in causing US recessions. *J. Money Credit Bank.* 49 (8), 1747–1776.
- Kilian, L., Zhou, X., 2018. Modeling fluctuations in the global demand for commodities. *J. Int. Money Finance* 88, 54–78.
- Kose, M., Otrok, C., Whiteman, C., 2003. International business cycles: World, region, and country-specific factors. *Amer. Econ. Rev.* 93 (4), 1216–1239.

- Liu, Y., Cai, W., Lin, X., Li, Z., Zhang, Y., 2023. Nonlinear El Niño impacts on the global economy under climate change. *Nature Commun.* 14 (1), 5887.
- Mainardi, S., 2011. Cropland use, yields, and droughts: spatial data modeling for Burkina Faso and Niger. *Agricult. Econ.* 42 (1), 17–33.
- McPhaden, M.J., Santoso, A., Cai, W., 2020. Introduction to El Niño Southern Oscillation in a changing climate. *El Niño South. Oscil. Chang. Clim.* 1–19.
- McPhaden, M., Zebiak, S., Glantz, M., 2006. ENSO as an integrating concept in earth science. *Science* 314 (5806), 1740–1745.
- Monfort, A., Renne, J.-P., Rüffer, R., Vitale, G., 2003. Is economic activity in the G7 synchronized? Common shocks versus spillover effects. *Common Shock. Versus Spillover Eff.* (November 2003).
- Montiel Olea, J., Stock, J., Watson, M., 2021. Inference in structural vector autoregressions identified with an external instrument. *J. Econometrics* 225 (1), 74–87.
- Morana, C., Sbrana, G., 2019. Climate change implications for the catastrophe bonds market: An empirical analysis. *Econ. Model.* 81, 274–294.
- Mueller, V.A., Osgood, D.E., 2009. Long-term consequences of short-term precipitation shocks: evidence from Brazilian migrant households. *Agricult. Econ.* 40 (5), 573–586.
- Newell, R., Prest, B., Sexton, S., 2021. The GDP-temperature relationship: implications for climate change damages. *J. Environ. Econ. Manag.* 108, 102445.
- NGFS, 2021. Climate change and monetary policy: initial takeaways. Network for Greening the Financial System.
- Noah, S., 2021. Why has climate economics failed us? Noahpinion (blog).
- Nordhaus, W.D., 1994. Expert opinion on climatic change. *Am. Sci.* 82 (1), 45–51.
- Noy, I., 2009. The macroeconomic consequences of disasters. *J. Dev. Econ.* 88 (2), 221–231.
- Oswald, A., Stern, N., 2019a. Why are economists letting down the world on climate change? *VoxEU.Org* (blog).
- Oswald, A., Stern, N., 2019b. Why does the economics of climate change matter so much, and why has the engagement of economists been so weak? *Royal Econ. Soc. Newsl.*
- Patnaik, I., Shah, A., Bhattacharya, R., 2011. Monetary Policy Transmission in an Emerging Market Setting, (no. 11–15), International Monetary Fund.
- Peersman, G., 2018. International Food Commodity Prices and Missing (Dis) Inflation in the Euro Area. CESifo Working Paper.
- Pezzey, J.C.V., 2019. Why the social cost of carbon will always be disputed. *WIREs Clim. Chang.* 10 (1), e558.
- Radetzki, M., 2006. The anatomy of three commodity booms. *Resour. Policy* 31 (1), 56–64.
- Ratti, R., Vespignani, J., 2016. Oil prices and global factor macroeconomic variables. *Energy Econ.* 59, 198–212.
- Ravn, M., Uhlig, H., 2002. On adjusting the Hodrick–Prescott filter for the frequency of observations. *Rev. Econ. Stat.* 84 (2), 371–376.
- Ropelewski, C.F., Halpert, M.S., 1987. Global and regional scale precipitation patterns associated with the El Niño/Southern Oscillation. *Mon. Weather Rev.* 115 (8), 1606–1626.
- Rosenzweig, C., Iglesias, A., Yang, X., Epstein, P., Chivian, E., 2001. Climate change and extreme weather events. *Glob. Chang. Hum. Health* 2 (2), 90.
- Saxegaard, M., Anand, R., Peiris, S., 2010. An Estimated Model with Macrofinancial Linkages for India, (no. 10–21), International Monetary Fund.
- Shi, Y., Su, J., 2020. A new equatorial oscillation index for better describing ENSO and Westerly wind bursts. *J. Meteorol. Res.* 34 (5), 1025–1037.
- Smith, S., Ubilava, D., 2017. The El Niño Southern Oscillation and economic growth in the developing world. *Global Environ. Change* 45, 151–164.
- Stern, N., Stiglitz, J., 2021. The Social Cost of Carbon, Risk, Distribution, Market Failures: An Alternative Approach. Technical Report, National Bureau of Economic Research.
- Stocker, T.F., Qin, D., Plattner, G.-K., Tignor, M., Allen, S.K., Boschung, J., Nauels, A., Xia, Y., Bex, V., Midgley, P., 2014. Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of IPCC the Intergovernmental Panel on Climate Change. Cambridge University Press.
- Tack, J., Ubilava, D., 2015. Climate and agricultural risk: measuring the effect of ENSO on US crop insurance. *Agricult. Econ.* 46 (2), 245–257.
- Timmermann, A., Oberhuber, J., Bacher, A., Esch, M., Latif, M., Roeckner, E., 1999. Increased El Niño frequency in a climate model forced by future greenhouse warming. *Nature* 398 (6729), 694–697.
- Ubilava, D., 2012. El Niño, La Niña, and world coffee price dynamics. *Agricult. Econ.* 43 (1), 17–26.
- Woodford, M., 2007. Globalization and Monetary Control. National Bureau of Economic Research.
- You, W., Guo, Y., Zhu, H., Tang, Y., 2017. Oil price shocks, economic policy uncertainty and industry stock returns in China: Asymmetric effects with quantile regression. *Energy Econ.* 68, 1–18.
- Zhang, Y., Liu, L., Lan, M., Su, Z., Wang, K., 2024. Climate change and economic policy uncertainty: Evidence from major countries around the world. *Econ. Anal. Policy* 81, 1045–1060.