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# Macroeconomic effects of El Niño diversity: a global vector autoregression (GVAR) approach

Solomos Solomou<sup>1,\*</sup>, Kun Tian<sup>2</sup>

<sup>1</sup>Faculty of Economics, University of Cambridge, Austin Robinson Building, Sidgwick Ave, Cambridge CB3 9DD, UK  
<sup>2</sup>Kent Business School, University of Kent, Sibson Building, Park Wood Rd, Canterbury CT2 7PE, UK

**ABSTRACT:** El Niño diversity is often depicted by the Central Pacific (CP) and Eastern Pacific (EP) El Niño types; these 2 distinct types of El Niño—Southern Oscillation (ENSO) regimes differ in their spatial structure, in their intensity and in the time profile of each event. We applied the global vector autoregression (GVAR) econometric framework to estimate the effects of El Niño diversity on national macroeconomic variables, including gross domestic product (GDP) and consumer price inflation, and global variables, such as world commodity prices and world oil prices. We used quarterly data for the period since ca. 1960, extending quarterly analysis significantly compared to the existing literature. Although the availability of quarterly economic data is limited for this period, we were able to study a set of 26 countries including ones that are directly affected by the El Niño cycle and others that are affected via climate teleconnections. ENSO diversity matters to macroeconomic outcomes; we found that CP El Niño shocks raise CPI inflation and non-oil commodity prices, and generate modest but widespread positive GDP responses across many mid- and high-latitude economies, whereas EP El Niño shocks have much weaker and less systematic effects on inflation, output and commodity prices. The implication of these results is that much of our existing knowledge on the economic effects of the ENSO cycle needs to be revisited to build a more consistent picture across countries and specific historical time periods.

**KEY WORDS:** El Niño · El Niño diversity · El Niño—Southern Oscillation · ENSO cycle · ENSO-economy linkages · Commodity prices · Economy—climate · Global shocks · GVAR models

## 1. INTRODUCTION

The El Niño—Southern Oscillation (ENSO) refers to cyclical variations in the temperature of the surface of the tropical Pacific Ocean resulting from interactions between the ocean and the atmosphere. The cycle of warming and cooling in this area has climate effects on extensive parts of the world, causing extreme weather events in different countries/regions. The focus of our analysis is on the economic implications of 'ENSO diversity' (Yu & Kao 2007, McPhaden et al. 2020). ENSO diversity is often depicted by the Eastern Pacific (EP) and Central Pacific (CP) ENSO types; these 2 distinct types of ENSO regimes differ in their spatial structure, in their intensity and in the time-profile of each event (Capotondi et al. 2020, Dieppois et al. 2021, Geng et al. 2022). Kao & Yu

(2009) concluded that EP and CP ENSO types have different generation mechanisms and a different location of SST anomalies: the EP ENSO type has its sub-surface anomalies located in the eastern equatorial Pacific whilst the CP ENSO type anomalies are located in the central Pacific.<sup>1</sup>

These different ENSO types also affect climate teleconnections. Alizadeh (2024) summarised the observed effects of ENSO diversity on climate teleconnections; for example, whilst EP ENSO is associated with heavy rain in western South America, CP ENSO

<sup>1</sup>As examples, the 1997/98 El Niño displayed extreme SST temperature changes in the eastern equatorial Pacific (and is thus classified as an EP ENSO); in contrast, the 2002/03 weaker El Niño was confined to the central equatorial Pacific (CP ENSO).

shifts this impact away from Latin America. We extend this result to consider whether ENSO diversity generates differentiated economic effects across countries.

Although the question of whether the ENSO cycle affects the macroeconomic outcomes of modern economies has been addressed by economists over many years, much of the existing research has focused on the canonical ENSO cycle, neglecting ENSO diversity. This literature has generated mixed results. Brunner (2002) studied the period 1963–1998, focusing on the global economic effects of El Niño working with a standard vector autoregression (VAR) model to explain variations in the weighted sum of GDP and average inflation for the G7 countries (Canada, France, Germany, Italy, Japan, UK and USA) and world commodity prices. The El Niño variations were found to explain 10–20% of the GDP and inflation movements of the G7 countries and accounted for 20% of the movements in real primary commodity prices—a 1 standard deviation (SD) El Niño surprise causing an increase of 3.5–4 percentage points in global commodity prices. In contrast, Laosuthi & Selover (2007) considered the relationship between El Niño fluctuations (measured by the Southern Oscillation Index [SOI]) and annual GDP and inflation for 22 countries over the period 1950–2000 and found only weak evidence of a relationship. In the case of the relationship between the El Niño and GDP growth, a significant effect was only found for South Africa, Australia, India and Mexico; GDP growth for all other countries was not affected by the SOI. Using quarterly data to analyse the El Niño–GDP growth relationship, Laosuthi & Selover (2007) reported weaker results, with only South Africa and Australia being affected.<sup>2</sup> In the study of inflation effects, at the annual frequency, over the period 1950–2000 they found only weak evidence of a relationship in the case of South Africa. Surprisingly, in the case of Australia, Japan and the UK, the El Niño process was found to Granger-cause a significant negative inflation relationship. Their analysis of quarterly data during 1957–2001 yielded even weaker results, with only the Philippines displaying a significant causal relationship. The summary of their results shows a weak and statistically insignificant relationship between El Niño and the consumer price index (CPI) inflation rates of the 22 countries (Laosuthi & Selover 2007). An examination of the relationship between El Niño and commodity prices found an insignificant effect on most

commodities. Consistent with these results, Berry & Okulicz-Kozaryn (2008) failed to find any evidence of macroeconomic effects of El Niño fluctuations on US business cycles over the period 1894–1999.

More recently, a number of studies using a variety of modern econometric methods have identified significant macroeconomic effects from ENSO fluctuations. Cashin et al. (2017) used the global vector autoregression (GVAR) econometric framework to analyse the global effects of the ENSO cycle and identified short-term inflationary effects on world commodity prices and world oil prices that persisted up to a 2 yr horizon, and statistically significant effects on GDP were observed for much of the world economy. They found that an El Niño shock had a negative impact on real economic activity in Australia, Brazil, Indonesia, Peru, the Philippines and South Africa. In contrast, the effects were positive for Argentina, Canada, China, Chile, Europe, Singapore, Thailand and the USA (Cashin et al. 2017). They also found effects on national CPI inflation rates for countries that are strongly teleconnected to the El Niño process, persisting over a 4-quarter period. Moreover, they identified significant spillover effects on non-teleconnected countries/regions arising from global economic spillovers (Cashin et al. 2017).

A number of studies using standard panel statistical methods have also identified significant macroeconomic output effects. Smith & Ubilava (2017) used distributed lag panel econometric methods to identify the effect of the ENSO cycle on economic growth in 69 developing countries using annual data for the period 1961–2015. They identified a non-linear effect from the ENSO cycle; a large El Niño event, measured as 1°C deviation in sea surface temperatures in the Niño 3.4 region of the equatorial Pacific, resulted in a significant 1–2% annual growth reduction during the El Niño phase (as part of the non-linear process, the La Niña phases were not found to be statistically significant). Given the lagged effects, the impact on economic growth rates was observed at an annual frequency over a number of years. Some recent empirical studies also found long-run effects from ENSO fluctuations. For example, Callahan & Mankin (2023) used a panel distributed lag model to quantify the effect of ENSO on growth in GDP per capita over the period 1960–2019 and found significant negative impact effects and persistent effects over a 5 and 10 yr horizon. The magnitude of the effects was directly related to the strength of teleconnections. Liu et al. (2023) estimated a panel distributed-lag model for an unbalanced panel of annual GDP per capita data for the period 1960–2019 (using the countries in the

<sup>2</sup>Costa Rica and Malaysia are also affected, but with unexpected longer lags.

World Bank data set). They evaluated the non-linear effects of the ENSO cycle using a quadratic relationship and found that the effect of the El Niño phase of the ENSO cycle persisted over a 3 yr period and cumulated to a large negative effect over the 3 yr, whereas the macroeconomic effects of the La Niña phase were statistically insignificant.

Dufrénot et al. (2024) used a global vector autoregression model with local projections to analyse the effects of the ENSO cycle. The advantage of the local projection method is that it allows for the distinction of the effects of an El Niño and La Niña state of the ENSO cycle. They constructed a weighted average of GDP and CPI inflation in 20 economies<sup>3</sup> (treating the Euro area as one economy) and used the ENSO shocks to consider the effects of an El Niño shock and a La Niña shock on global inflation and output. The effect of an EN shock on output was positive, becoming statistically significant in month 9; the effect of a La Niña shock was insignificant. The effect of an El Niño shock on inflation was statistically significant in the second half of the year of the shock, with the magnitude of the effect ranging between 0.2 to 0.4%. The La Niña state of the ENSO cycle was also inflationary, with a more immediate effect being identified. The magnitude of the effect was similar across La Niña and El Niño states. They also considered the effect on global commodity prices, focusing on international oil and food prices (measured in real terms, deflated with USA consumer prices). A El Niño shock raised real oil prices significantly (by 10%) in the year of the shock but had a limited effect on global food prices, raising them by 2% after 6 mo. A La Niña shock raised food prices by 5% and oil prices by 10% in the second half of the year.

In this study, we contribute to the economic analysis of the ENSO cycle in 3 significant ways. First, we focus on the economic effects of ENSO on a set of response variables, including GDP and inflation at the national level and on global commodity prices. This broad focus allows us to relate our results to much of the existing literature.

Second, we focus on evaluating the economic implications of 'ENSO diversity'. Different ENSO types affect climate teleconnections, which, in turn, may generate differentiated economic effects across countries/regions. The question we analyse in this

paper is whether ENSO diversity affects macroeconomic outcomes. With the exception of the work of Callahan & Mankin (2023), ENSO diversity has been neglected in the economic analysis of El Niño. We complement the work of Callahan & Mankin (2023), who focused on real GDP per capita effects, by developing the analysis of ENSO diversity using a broader set of economic response variables: considering GDP, inflation and world commodity price effects in the GVAR empirical framework. This empirical framework allows us to evaluate the national economic effects of ENSO diversity. In addition to focusing on ENSO diversity, we also provide an analysis using more conventional measures of ENSO such as Niño 3.4. This allows us to evaluate the importance of ENSO diversity in explaining some of the findings in the existing literature.

Thirdly, given the global effects of the ENSO cycle, and more generally considering an inter-related global economic system, we worked with the GVAR methodology, allowing us to model these global linkages. A key problem in modelling climate–economy interactions is the difficulty of modelling the effect of global variables (such as ENSO shocks) on national economies that are inter-related in the global economy via trade and capital flows. The GVAR methodology allows us to model some of these interaction effects (Pesaran et al. 2004, Pesaran & Smith 2006, Chudik & Pesaran 2016). The GVAR framework has 3 important useful features: first, global shocks, such as the ENSO variations, that affect many parts of the world either directly or via climate teleconnections can be modelled as exogenous global shocks to an economic system; second, global inter-relatedness of economies is at the heart of these models, allowing us to model the effects of a global shock on the world economy (defined statistically as a set of inter-related economies); third, unlike standard panel models, GVAR models are able to estimate heterogeneous effects across countries. A set of trade weights captures the cross-national linkages, allowing us to model spillover effects across countries. As noted above, the GVAR model has already been used to quantify the impact of the ENSO cycle for the modern period. Cashin et al. (2017) applied the GVAR framework to estimate the macroeconomic effects of El Niño fluctuations on 21 economies/regions of the global economy (they treated Europe as one region)<sup>4</sup> using

<sup>3</sup>The 20 economies include: Brazil, Switzerland, Chile, Canada, China, Columbia, Czech Republic, the Euro zone (19 countries), UK, Hungary, Ireland, India, Israel, Japan, South Korea, Poland, Russia, Sweden, Turkey and the USA. The data are monthly and cover the period from January 1999 to March 2022.

<sup>4</sup>Cashin et al. (2017) noted that Europe is not directly affected by the ENSO cycle. Here, we were guided by evidence that Europe is affected by ENSO teleconnections (Brönnimann 2007, Alizadeh 2024).

quarterly data for the period 1979(Q2)–2013(Q1). We contribute to the GVAR evaluation of the ENSO cycle in a number of ways. First, we complement the work of Cashin et al. (2017) by focusing explicitly on the implications of ENSO diversity, by considering the EP and CP El Niño types. Second, we extend the quarterly data set to consider a longer time period, covering the period 1960–2019, allowing us to capture more ENSO cycles. The longer time period is particularly useful to capture more time observations of ENSO diversity. Given the length of the time period, we also consider the effects of changing weights to capture how economic spillovers change over long historical periods. Finally, given that VAR models are not unique, we introduce new variables into the analysis that help us model how the ENSO shocks are transmitted.<sup>5</sup>

To implement this method, we were able to build a quarterly data set for 26 countries for the period 1960(Q1)–2019(Q4). The data set includes quarterly data for GDP, CPI inflation, nominal and real effective exchange rates, global oil prices, global non-oil commodity prices and information on the CP and EP ENSO variations (the data sources are described in the Appendix).<sup>6</sup> The country coverage includes Argentina, Australia, Austria, Belgium, Brazil, Canada, Chile, Finland, France, Germany, India, Italy, Japan, Korea, Mexico, Netherlands, Norway, New Zealand, Philippines, South Africa, Spain, Sweden, Switzerland, Turkey, UK and the USA. It is important to note that our empirical study relies on a sample of countries for which consistent quarterly macroeconomic data are available, which tends to bias coverage towards higher-income and more data-rich economies. This limitation reflects the inherent challenges in assembling long-span quarterly data, particularly for lower-income and tropical countries that are often more directly exposed to climate shocks. As such, we have not been able to include all countries that are impacted by the ENSO cycle—for example, Peru, Ecuador and Indonesia could not be included in this GVAR study.<sup>7</sup> Despite this constraint, we feel that our 26-country study allows us to consider a broad set of countries that are impacted by ENSO processes

either directly or via climate teleconnections. Moreover, the GVAR model captures the global economic connections between these countries using trade weights to capture country interactions. One significant advantage of our selection of countries is that the sample represents much of global income, allowing us to capture the global effects of ENSO.

## 2. METHODOLOGY

### 2.1. Construction of orthogonal CP and EP ENSO indices

To more accurately capture the distinct spatial structures of CP and EP El Niño events, we used the data set developed by Kao & Yu (2009) and extended by Yu & Kim (2010). Their data were derived using the regression–empirical orthogonal function (EOF) method.<sup>8</sup> This approach addresses a key challenge in ENSO research: the spatial and temporal correlation between CP and EP sea surface temperature (SST) anomalies, which complicates efforts to isolate their individual economic effects using conventional Niño indices such as Niño 3, Niño 4 and Niño 3.4.

The core idea of this method is to remove the influence of one ENSO type from the SST anomaly field before performing EOF analysis, thereby allowing the leading EOF mode to reflect the structure of the other ENSO type. Specifically, to extract the CP ENSO signal, Kao & Yu (2009) first regressed the global SST anomaly field on the Niño 1+2 index (defined over 0–10°S, 90–80°W), which is widely accepted as a proxy for EP ENSO variability. The fitted component of this regression is interpreted as the portion of SST anomalies attributable to EP ENSO. This fitted EP component is then subtracted from the total SST anomaly field. The resulting residuals, which remove the EP ENSO signal, are subjected to EOF decomposition. The leading EOF mode from this residual SST field captures the dominant spatial structure of CP ENSO, and the corresponding principal component time series is extracted as the CP ENSO index.

<sup>5</sup>This multivariate data set in a GVAR setting implies that we have a system of variables affected by climate shocks. One should be aware of the 'over-controlling problem' noted by Dell et al. (2014), resulting from climate variables impacting other control variables in the economic model. The GVAR model deals with the 'over-controlling problem' by modelling the complex interactions between climate and economy.

<sup>6</sup>Interest rate data also exist for this period but for a more limited set of countries.

<sup>7</sup>We recognise that this is a problem that needs to be addressed—as an extension of this study, we are developing annual data sets that would allow us to consider a broader set of countries within a similar GVAR framework.

<sup>8</sup>A similar data set for CP and EP ENSO was produced by Takahashi et al. (2011), who also used the empirical orthogonal function method. The 2 data sets follow each other closely: at the monthly frequency, the correlation coefficient for the 2 EP series is 0.93 (and 0.90 for the 2 CP measures).

Kao & Yu (2009) and Yu & Kim (2010) followed a symmetric procedure to obtain the EP ENSO index. In this case, the SST anomalies are regressed on the Niño 4 index (centred on 5° S–5° N, 160° E–150° W), which represents CP ENSO variability. The fitted CP component is then subtracted from the total SST anomalies, and EOF analysis is performed on the residuals. The first EOF mode derived from this residual field isolates the spatial pattern associated with EP ENSO events, and its principal component time series is used as the EP ENSO index. This orthogonalisation process reduces multicollinearity and enhances the identification of the differential macroeconomic effects of CP and EP El Niño episodes.

## 2.2. GVAR Models

To model the effects of the ENSO cycle on economies, we used GVAR models,<sup>9</sup> which are capable of capturing a number of important aspects of the ENSO–economy linkages. Firstly, the effects of ENSO variations are likely to display national heterogeneity as the effects of rainfall and temperature variations differ across economies with different economic structures. These effects will vary by country, partly because different sectors have differing sensitivities to rain and temperature. Although many countries share some common trends in sectoral structures (such as the path of de-industrialisation), the sectoral structures of economies differ significantly. Second, given the global reach of the ENSO cycle, we would expect that any national effects would have spillover effects across countries. Modelling this network of linkages in a GVAR model allows us to identify the interconnectedness of countries. In this paper, we achieved this by modelling the changing linkages via changing trade weights since the 1950s that affected the changing international business cycle features over the post-war period.

The GVAR model is a sophisticated econometric technique designed to analyse complex interdependencies and dynamic interactions among multiple time series across different countries or regions (Chudik & Pesaran 2016). The GVAR framework extends the traditional VAR model to a global context, accommodating the interconnectedness of economic variables in a multi-country setting. This method has become increasingly valuable for policy analysis,

forecasting, and understanding the transmission of global shocks.

At its core, the GVAR model integrates individual country-specific VAR models into a cohesive global system. Each country model includes both domestic variables and foreign variables, which are constructed as weighted averages of corresponding variables from other countries. This structure allows us to capture spillover effects and feedback loops between countries, reflecting the reality of economic globalization. The GVAR model is represented by the following 4 key equations:

(1) Country-specific VARX ( $p, q$ ) model:

For each country  $i$  (where  $i=1, \dots, N$ )

$$y_{it} = \alpha_i + \sum_{j=1}^p A_{ij} y_{it-j} + \sum_{k=0}^q B_{ik} x_{it-k} + \sum_{l=0}^r C_{il} d_{t-l} + u_{it} \quad (1)$$

where  $y_{it}$  is a  $k_i \times 1$  vector of domestic endogenous variables for country  $i$ .  $x_{it}$  is a  $m_i \times 1$  vector of foreign exogenous variables for country  $i$ .  $\alpha_i$  is a  $k_i \times 1$  vector of intercept terms.  $d_t$  is a  $d_t \times 1$  vector of variables from the dominant unit.  $A_{ij}$  are  $k_i \times k_i$  coefficient matrices for domestic lags.  $B_{ik}$  are  $k_i \times m_i$  coefficient matrices for foreign variables.  $C_{il}$  are  $k_i \times d$  coefficient matrices for dominant unit variables.  $u_{it}$  is a  $k_i \times 1$  vector of error terms. Each country is represented by a VAR model that includes a set of endogenous domestic variables, such as real GDP, inflation and the real exchange rate. Following Cashin et al. (2017), we modelled the global commodity market by including both the real oil price and real non-oil commodity price as endogenous variables. We also included weakly exogenous variables in this global commodity market model, such as real GDP, inflation rate and the real exchange rate (all 3 weakly exogenous variables were constructed by using purchasing power parity GDP weights).

(2) Construction of foreign variables:

The foreign variables for country  $i$  are constructed as weighted averages of the corresponding domestic variables of other countries:

$$x_{it} = \sum_{j \neq i} w_{ij} y_{jt} \quad (2)$$

where  $w_{ij}$  represents the weights that capture the extent of economic linkages between countries  $i$  and  $j$ . These weights can be based on trade shares, financial linkages, or other relevant criteria. We applied trade weights in our empirical estimation.

(3) Including a dominant unit in the GVAR:

The dominant unit is modeled separately, typically with its own VAR model:

$$d_t = c + \sum_{j=1}^{p_d} D_j d_{t-j} + e_t \quad (3)$$

<sup>9</sup>We estimated the GVAR model by using the GVAR toolbox constructed by Smith & Galesi (2014).

where  $\mathbf{d}_t$  is a  $d \times 1$  vector of variables from the dominant unit.  $\mathbf{c}$  is a  $d \times 1$  vector of intercept terms.  $\mathbf{D}_j$  are a  $d \times d$  coefficient matrices for the lags of dominant unit variables.  $p_d$  denotes the lag order of the dominant-unit VAR.  $\mathbf{e}_t$  is a  $d \times 1$  vector of error terms. We modelled the CP and EP measure of ENSO in the dominant unit.

(4) Global VAR model:

Combining the country-specific VARX models with the dominant unit model, the global system can be represented as:

$$\mathbf{Y}_t = \mathbf{A}(L)\mathbf{Y}_t + \mathbf{B}(L)\mathbf{X}_t + \mathbf{C}(L)\mathbf{D}_t + \mathbf{U}_t \quad (4)$$

where  $\mathbf{Y}_t$  is the stacked vector of all domestic variables across countries.  $\mathbf{X}_t$  is the stacked vector of all foreign variables.  $\mathbf{D}_t$  is the vector of dominant unit variables.  $\mathbf{A}(L)$ ,  $\mathbf{B}(L)$ , and  $\mathbf{C}(L)$  are lag polynomial matrices.  $\mathbf{U}_t$  is the stacked vector of error terms.

To estimate the macroeconomic effects of El Niño fluctuations, we employed a GVAR model that incorporates quarterly data for all countries in our sample. The GVAR framework allows for rich interdependencies across countries by combining country-specific VAR models, each of which includes weakly exogenous foreign variables constructed as trade-weighted averages. Once the country-specific models are estimated, they are stacked and solved consistently to form the global system. To assess the dynamic impact of El Niño shocks, we computed generalised impulse response functions (GIRFs), which trace the responses of macroeconomic variables to 1 SD shocks to the Niño index,<sup>10</sup> while accounting for contemporaneous correlations across innovations.

<sup>10</sup>The Niño index is treated as an exogenous variable in the GVAR framework, reflecting its origin in external climatic processes not influenced by the macroeconomic variables in the model. To generate a 1 SD shock to the Niño index, we perturb the innovation in its own process by its empirical SD, which is computed directly from the estimated residuals of the Niño index series. Since the index is exogenous, this shock is imposed externally and propagated through the global system via the estimated country-specific VARX\* models (\* denoting the inclusion of foreign star variables), where the Niño index enters as a weakly exogenous regressor. The shock is introduced as a one-off innovation at time  $t$ , holding all other contemporaneous innovations fixed, and the resulting responses of endogenous macroeconomic variables are traced through the GIRFs. These GIRFs are computed using a residual-based bootstrap with multiple replications, allowing us to construct confidence intervals and assess the statistical significance of the estimated dynamic effects. This approach ensures that the climate-induced perturbation is cleanly identified while preserving the historical joint distribution of the remaining shocks in the system.

Importantly, these GIRFs are simulated using a bootstrap procedure with multiple replications, enabling us to construct confidence intervals and ensure robustness of the results without relying on arbitrary event classification. This approach takes full advantage of the continuous variation in El Niño conditions and preserves statistical power by utilising the complete time series of the ENSO variations.

### 3. EMPIRICAL RESULTS: THE MACROECONOMIC EFFECTS OF ENSO DIVERSITY

As noted above, the effects of ENSO diversity were analysed using the CP and EP measures of ENSO. For comparison, in Supplement 1 at [www.int-res.com/articles/suppl/c095p073\\_supp.pdf](http://www.int-res.com/articles/suppl/c095p073_supp.pdf), we also report the results when using the canonical Niño 3.4 measure (neglecting ENSO diversity) that has been used extensively in the literature. We begin with a focus on CP ENSO variations. We first focus on a model explaining quarter-on-quarter inflation.<sup>11</sup> Fig. 1 shows the effect of a 1 SD shock to El Niño on national inflation rates measured in this way. The effects are generally small in magnitude and statistically insignificant for most countries. The major exceptions are India, which sees a 0.12% increase in quarterly inflation by Q2; Argentina, which sees a fall in quarterly inflation of 0.9% by Q4; the USA, which sees a small inflationary effect of 0.02% by Q4; and Turkey, which sees a rise in quarterly inflation of 0.4% by Q2. The effect on most European countries is small and statistically insignificant.<sup>12</sup> The weak effects on quarterly inflation rates are also reflected in weak inflation effects on world commodity prices. The real non-oil commodity price index rises significantly by approximately 1.0% by Q8 but remains weak and statistically insignificant up to Q4 (see Supplement 3). In contrast, real oil prices fall by 2% by Q4. The inverse movements and lack of synchrony act to ease overall inflationary pressures on the global economy from commodity prices.

Fig. 2 shows the effect of a 1 SD shock to a CP El Niño on national inflation rates measured as the 4-quarter inflation rate.<sup>13</sup> Three features stand out: first, the effects are heterogeneous across countries;

<sup>11</sup>The use of quarter-on-quarter data is common in quarterly analysis; for example, it is found in the quarterly data analysis of Cashin et al. (2017). The key economic variables in this model are quarterly data for GDP, inflation, the real effective exchange rate, world oil prices and world (non-oil) commodity prices.

<sup>12</sup>The exceptions are the UK, Austria and Belgium, which see a decrease in inflation by 0.05% by Q4.

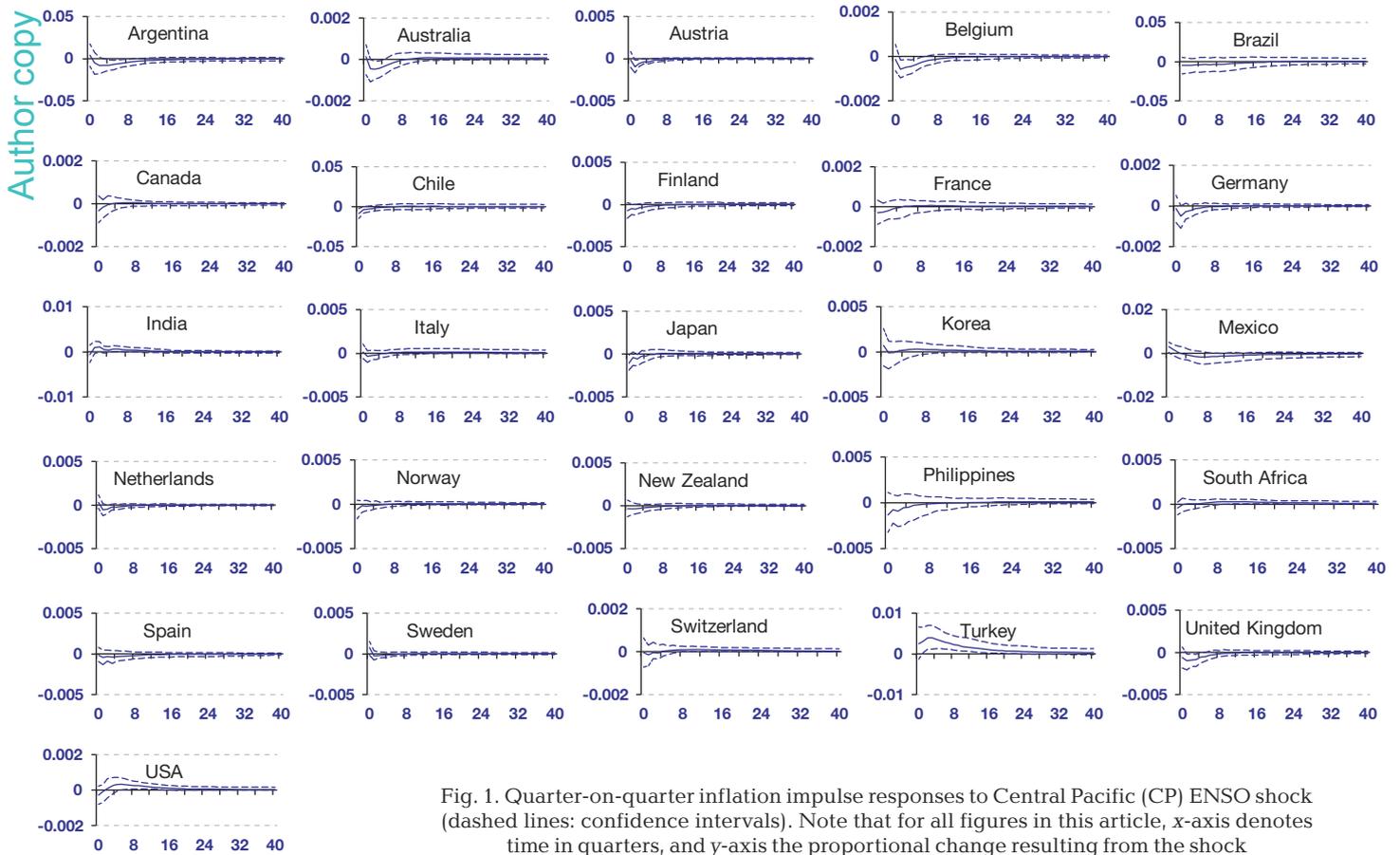


Fig. 1. Quarter-on-quarter inflation impulse responses to Central Pacific (CP) ENSO shock (dashed lines: confidence intervals). Note that for all figures in this article, x-axis denotes time in quarters, and y-axis the proportional change resulting from the shock

second, for a number of countries, the effects are small in magnitude but are statistically significant; finally, for many countries, the effects are statistically insignificant. A large statistically significant effect is observed for a few countries: India (inflation increases 0.5% by Q5); Turkey (0.6% by Q13); Chile (1% by year 3); and Mexico (0.5% by Q18). The inflation effect on European countries is small in magnitude (between 0.1 and 0.2%) and only becomes statistically significant in years 2 to 3 of the time profile, suggesting that the outcome is determined by global spillovers.

For a number of countries that are directly affected by the ENSO cycle, including Argentina, Brazil, New Zealand, and the Philippines, the effect on inflation is statistically insignificant. The inflation effect on Australia is small in magnitude and builds slowly (0.1% by Q15). For some teleconnected countries, the effect is statistically significant but small in magnitude: the USA sees a 0.2% effect by Q8 and South Africa sees a 0.1% effect by Q11. Clearly, the evidence suggests that the ENSO cycle impacts inflation in the macroeconomy at the yearly frequency, and using the quarterly structure of the data in this way allows us to identify these effects.<sup>14</sup>

The positive effects on national inflation rates are also reflected in inflation effects on world commodity prices. The non-oil real commodity price index rises significantly by approximately 1.5% by Q8 and the positive effect remains significant over a 3 to 4 yr horizon. In contrast, the effect on real oil prices is negative but statistically insignificant (see Supplement 3).

Fig. 3 shows the effect of a 1 SD shock to the CP El Niño on GDP as the response variable (using the annual structure of the quarterly data). The estimated effects vary in magnitude and are heterogeneous across countries. Most countries display a positive response function. The countries with the biggest effects are Argentina (0.4% by Q8), Brazil (0.5% by Q13), Japan (0.6% by Q8), Mexico (0.6% by Q14) and

<sup>14</sup>This raises an important methodological point. Clearly, as we focus on high-frequency data, we can observe the high-frequency time-profile of how ENSO affects the economy. However, if the effects of ENSO build over time, then aggregating the response variable (such as inflation) using the monthly or quarterly data to the yearly frequency (using the quarterly structure of the data) has advantages by reducing the noise of the high-frequency data.

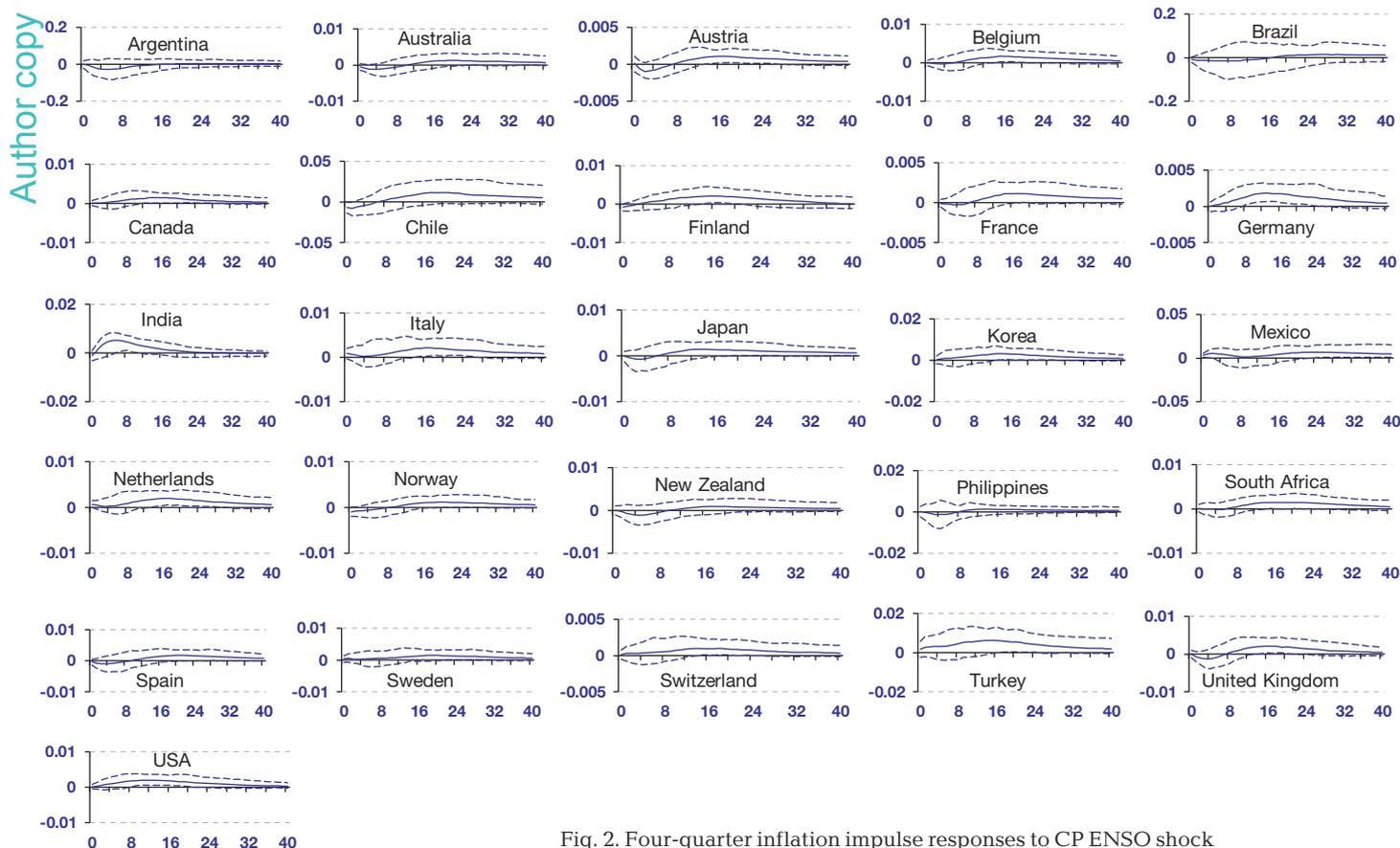


Fig. 2. Four-quarter inflation impulse responses to CP ENSO shock

Turkey (0.4% by Q6). European countries see a positive impulse-response on GDP that ranges between 0.1 and 0.4%, with peaks between Q8 and Q12. The USA and Canada see a positive effect of 0.3% by Q8. The magnitude of the effect on Chile and India is small and statistically insignificant. Countries that are directly affected by the ENSO cycle generally display a positive response function that is small in magnitude: New Zealand (0.1% effect by Q8); the Philippines (0.27% effect by Q12); Australia (0.1% effect by Q8).

Next we consider the effects of EP ENSO variations. Fig. 4 displays the effects on inflation measured as the quarter-on-quarter inflation rate. For most countries, the effects are small in magnitude and statistically insignificant. An exception is the case of Argentina, with a 1% effect on quarterly inflation by Q2. The weak effect on national inflation rates is also reflected in inflation effects on world commodity prices. The effect on the non-oil commodity price index is small in magnitude and statistically insignificant (see Supplement 3); the effect on oil prices is negative, falling by 1% by Q5, but this effect is statistically insignificant.

Fig. 5 shows the effect of a 1 SD shock to the EP El Niño on national inflation rates measured as the 4-quarter inflation rate. With only a few exceptions, all of the effects are small in magnitude and statistically insignificant. A large positive significant effect is identified for Argentina (a 4% median effect on inflation by Q4).<sup>15</sup> India and the Philippines display a positive impulse-response function with a 0.4% peak effect, but the results are statistically insignificant.<sup>16</sup> The evidence from world commodity prices suggests that global non-oil commodity prices are not impacted, and world oil prices see a negative effect of 1.0% by Q12 (see Supplement 3).

Fig. 6 shows the effect of a 1 SD shock to the EP El Niño on GDP. With the exception of Korea, the effects are small in magnitude and statistically insignificant; Korea sees a fall in GDP of 0.3% by Q4.

<sup>15</sup>This large magnitude needs to be understood in terms of the hyperinflation experience of Argentina, which will impact these mean estimates.

<sup>16</sup>In Supplement 2, we consider the non-linear effects of ENSO. Focusing on the El Niño phase of the cycle, this effect on India and the Philippines is significant.

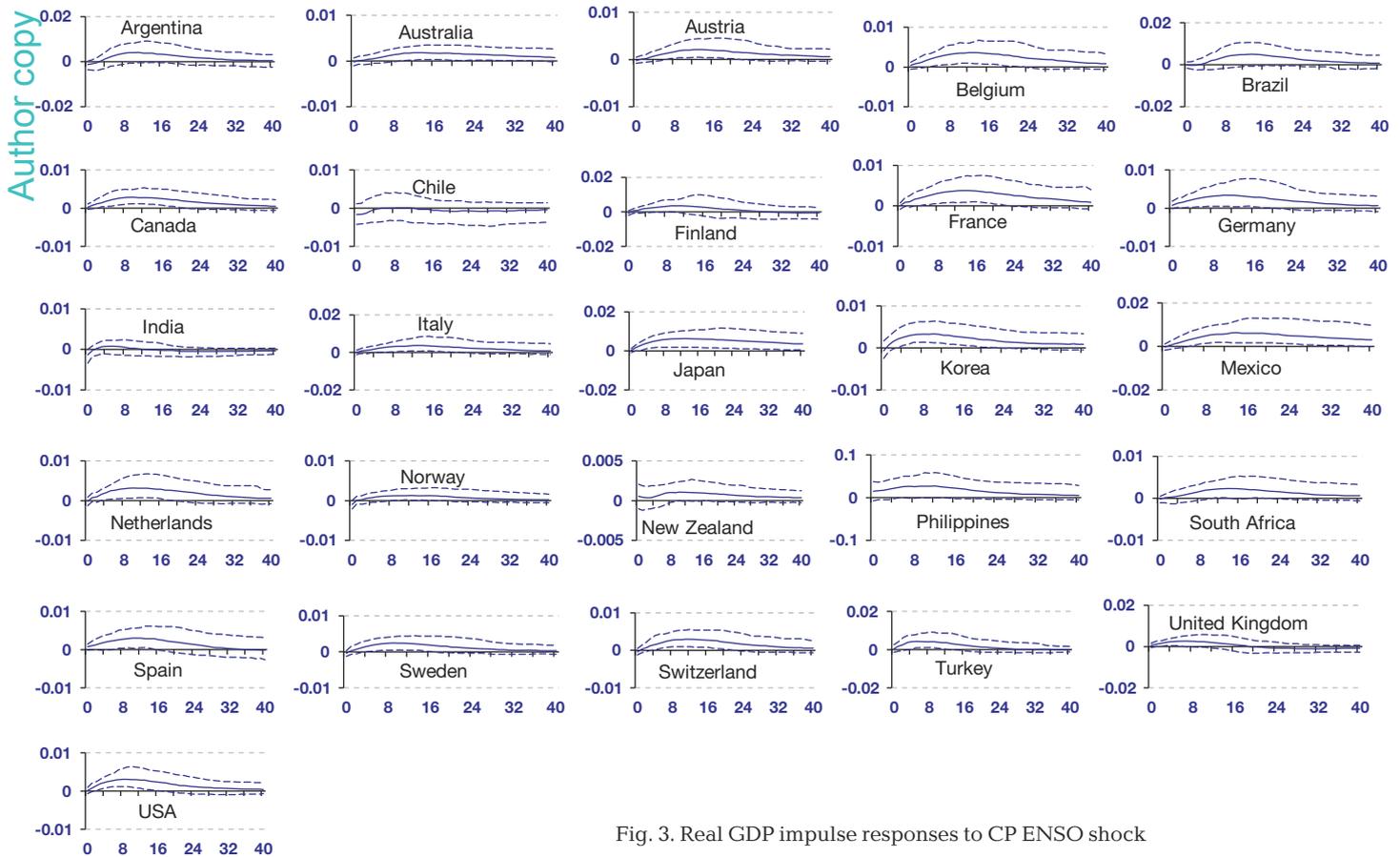


Fig. 3. Real GDP impulse responses to CP ENSO shock

In summary, it is clear that ENSO diversity matters when evaluating the macroeconomic effects of El Niño. The results reported here suggest that in the period since ca. 1960, the effects of the CP El Niño are dominant for the set of countries we were able to consider in this study. With a few exceptions, EP events have not had significant effects on inflation, GDP or world commodity prices.<sup>17</sup> This suggests that many of the existing results on the ENSO cycle need to be re-evaluated. To the extent that ENSO diversity is important, neglecting this feature may result in biased

<sup>17</sup>This result needs to be interpreted with care. The CP and EP ENSO process results in time-varying fluctuations. In the period since ca. 1960, there have only been a few large EP Niño variations; CP ENSO variations have been dominant in the recent post-war period. Hence, this result simply summarises the best estimate of the mean effects across the whole period ca. 1960–2019—it does not capture all of the information of the EP ENSO cycle. To study this feature further, we have to consider longer historical time horizons, allowing us to observe more EP ENSO cycles.

<sup>18</sup>In Supplement 1, we also consider the effects of ENSO neglecting this diversity using the Niño 3.4 measure as a measure of the ENSO cycle. The results indicate significant differences from the baseline results reported in this paper.

empirical estimates.<sup>18</sup> This key result seems paradoxical given that EP ENSO events display large El Niño phases. Here we consider 3 aspects as plausible explanations for this result, which also guide future research:

First, several studies (Ashok et al. 2007, Strnad et al. 2022, Alizadeh 2024) have shown that CP and EP events have very different climate teleconnections. In particular, CP events can trigger broader or more persistent atmospheric responses over the mid-latitudes, where many advanced economies are located. The 26-country sample we were able to study at the quarterly frequency includes many mid- and high-latitude economies that experience these CP-driven teleconnections. In contrast, the teleconnections of EP events are focused in the tropics; as noted in Section 1, many countries could not be included in our high-frequency study. Hence, the importance of CP-ENSO identified in our study partly reflects the sample of countries we were able to consider using quarterly data; many of these countries are teleconnected to the CP-ENSO variations. The takeaway message from this result is that researchers in this area need to build high-frequency data sets for a

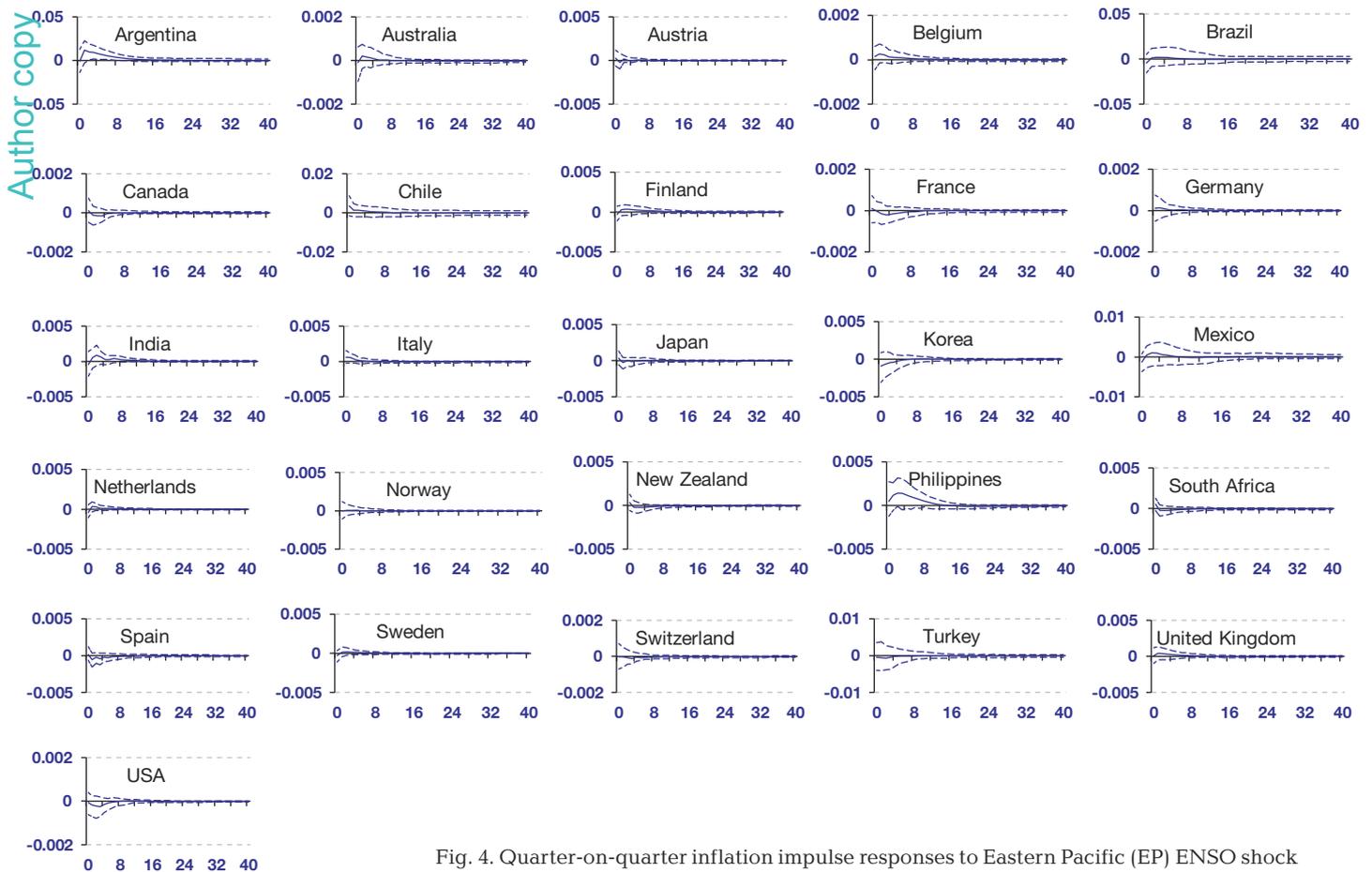


Fig. 4. Quarter-on-quarter inflation impulse responses to Eastern Pacific (EP) ENSO shock

broader set of countries to consider the effects arising from EP events.

Second, over long historical periods, the evidence suggests that the frequency of CP and EP events displays time variation. There is growing evidence that the frequency of CP events has increased significantly since ca. 1980 (Yu & Kim 2013, Pascolini-Campbell et al. 2015, Freund et al. 2019). Our sample period was 1960–2019; hence, for most of this time period, CP-type events were dominant. This means that the teleconnections activated would mainly affect our sample of countries. The implication of this is that the results we have documented here are specific to this historical episode. The takeaway message is that we need to build long-term historical data sets to consider the effects arising from EP events.

Finally, although there were a few large EP ENSO events in our sample period (1982–3 and 1997), we should consider the whole movement of the CP ENSO cycle. One of our results is that both the warming and cooling phases of the CP ENSO cycle have economic effects; El Niño and La Niña are both important in economic effects. Overall, the variance of the CP

ENSO cycle is comparable to the EP ENSO cycle.<sup>19</sup> Hence, the significant effects identified for the CP ENSO cycle are consistent with the evidence.

To evaluate the robustness of our results, we estimated a number of sensitivity tests. First, we estimated a model using the Niño 3.4 index for comparison with our baseline results. The Niño 3.4 results are summarised in Supplement 1 and are very different from the results we estimated when we modelled the effects of ENSO diversity. Together with the result that ENSO diversity generates meaningful results, we argue that using a fixed region to measure the ENSO cycle is prone to produce misleading results because it fails to fully capture the nature of climate teleconnections. One of the results often reported in economic studies of ENSO is that the measure of El Niño does not affect the key results (Brunner 2002). We have shown that this is because ENSO diversity has been neglected. Identifying ENSO diversity using the CP and EP mea-

<sup>19</sup>During 1960Q1–2019Q4, the variance for CP-ENSO was 0.979 and the variance for EP-ENSO was 0.986.

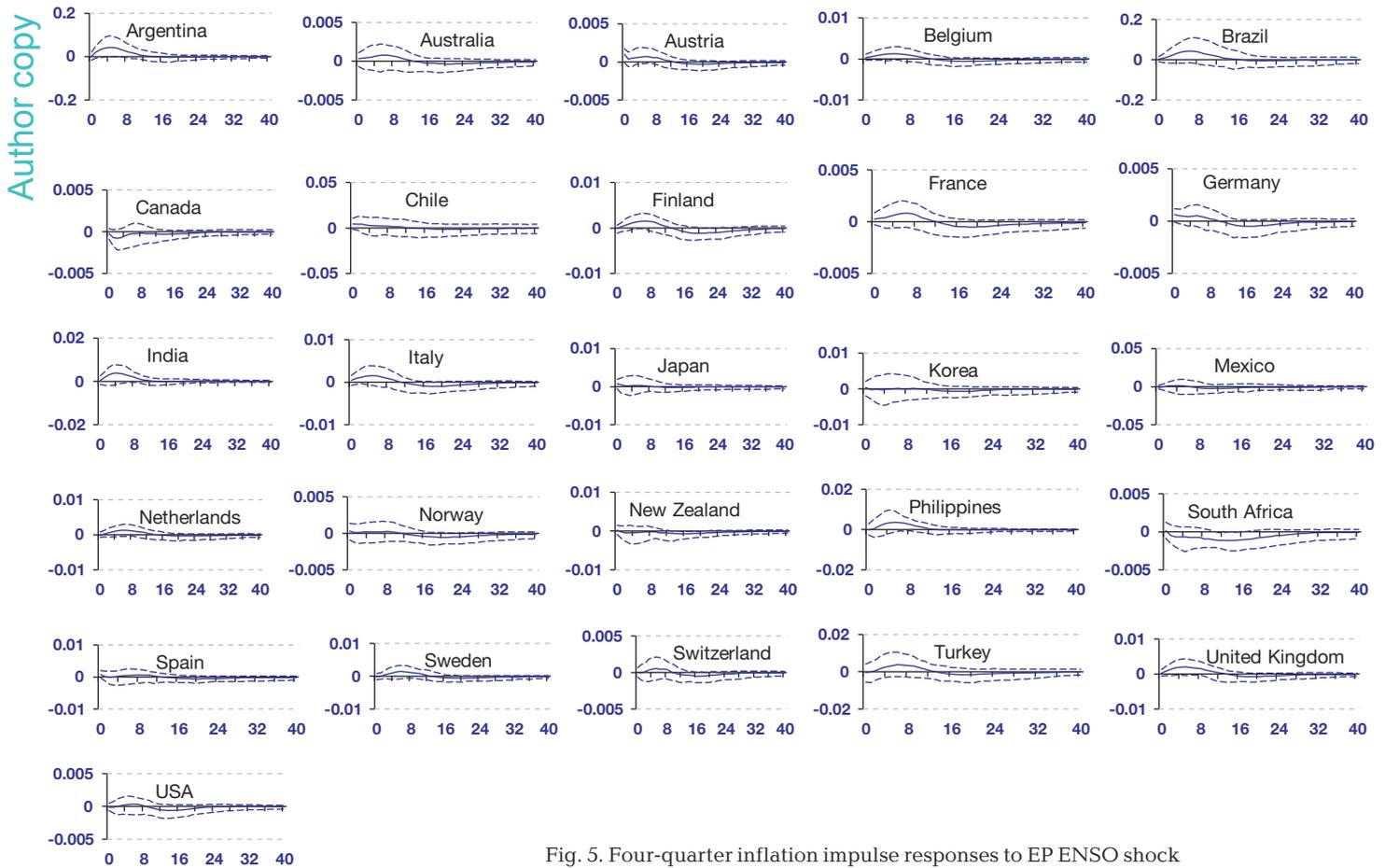


Fig. 5. Four-quarter inflation impulse responses to EP ENSO shock

sure generates very different economic effects to fixed-region measures of ENSO (such as Niño 3.4).

Second, we considered whether non-linearity matters to the estimates that we report using the GVAR model. In Supplement 2, we report the results of estimations to evaluate whether non-linear effects can be identified in the effects of different phases of the ENSO cycle by distinguishing its cold and warm phases. Our key finding here is that the linear model provides a good approximation, although some non-linear effects are identified for particular countries. Clearly, the aspect of non-linear effects needs further analysis using techniques that can comment more explicitly on this feature; in this paper, we simply adapted the GVAR model to comment on possible non-linearities to show that our results are meaningful. Further analysis of non-linearity using alternative frameworks would be helpful to get a better understanding of the effects of ENSO diversity on macroeconomic outcomes.

Thirdly, the GVAR model relies on global connections to model how shocks propagate across countries. Trade weights have been used to measure the strength

of these economic global connections. Over the long historical period we have considered here (1960Q1–2019Q4), there have been significant changes in these trade links, as global trading arrangements have changed significantly over time. We have built trade weights for the whole period since ca. 1950, allowing us to vary the trade weights to capture these changing global linkages. Our set of baseline results are robust to these temporal changes in global trade linkages.

Finally, working with a GVAR model, we acknowledge that the set of possible variables to model inflation and GDP is not unique. The limitations on the availability of post-war quarterly data means that we have a limited set of quarterly variables that can be considered. Our model uses quarterly GDP, global real commodity prices, global real oil prices, real effective exchange rates and nominal effective exchange rates. Because the VAR models are not unique, we included a number of combinations of these variables that have different advantages and disadvantages. For example, we estimated our baseline models using quarterly GDP, global real commodity prices, global real oil prices and real effective exchange rates. We

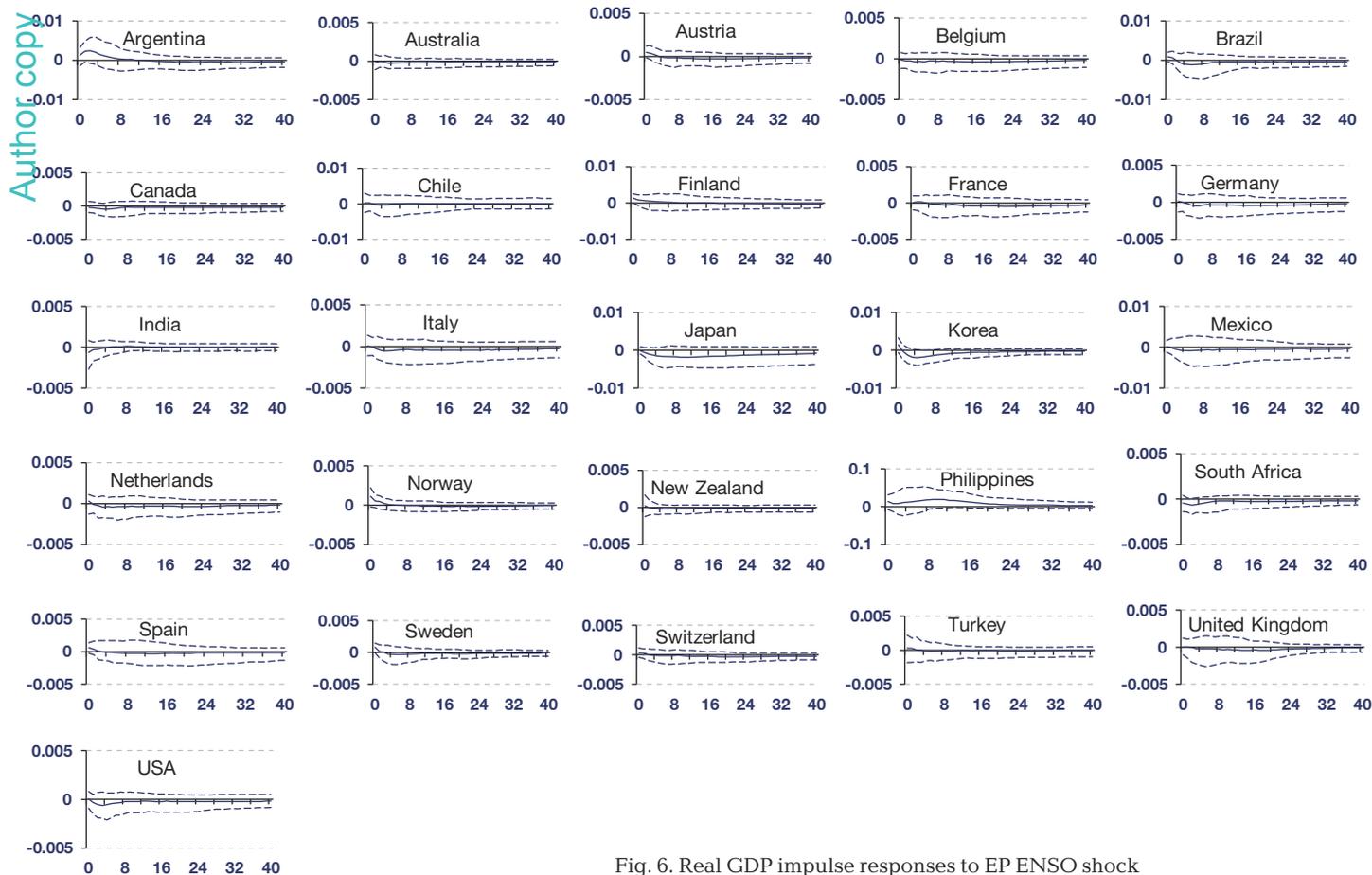


Fig. 6. Real GDP impulse responses to EP ENSO shock

also estimated models using nominal effective exchange rates, since nominal effective exchange rates may better capture the response of inflation. The results suggest that the estimated effects are affected by using different combinations of variables. For example, in using the nominal effective exchange rate data instead of the real effective exchange rate, the time profile of effects and significance level is impacted. This suggests that investing in building a broader high-frequency data set for the post-war period will add value to further research in this area.

#### 4. DISCUSSION AND CONCLUSIONS

ENSO diversity matters to the analysis of El Niño effects on macroeconomic outcomes. We have shown that CP and EP ENSO types have differentiated effects on inflation, GDP and global commodity prices. The neglect of ENSO diversity in the existing literature may help to reconcile some of the conflicting results that have been reported.

Focusing on GDP effects<sup>20</sup> arising from shocks to CP ENSO types, we identified positive effects on Argentina (0.4% by Q8), Brazil (0.5% by Q13), Japan (0.6% by Q8), Mexico (0.6% by Q14), Turkey (0.4% by Q6), a number of European countries (the effect ranged between 0.1 and 0.4%, with peaks between Q8 and Q12).<sup>21</sup> The USA and Canada saw a similar effect of 0.3% by Q8. The magnitude of the effect on Chile and India was small and statistically insignificant. Countries that are directly affected by the ENSO cycle generally displayed a positive response function that was small in magnitude: Australia (0.1% effect by Q8), New Zealand (0.1% effect by Q8) and the Philippines (0.27% effect by Q12). In contrast, the effects of EP ENSO variations on GDP generated insignificant results (the exception was Korea, with a decrease in GDP of 0.3% by Q4).

<sup>20</sup>Since the 4-quarter changes yielded more meaningful results, we focus on these results here.

<sup>21</sup>Dufrénot et al. (2024) reported positive effects for El Niño shock on GDP and insignificant effects for La Niña shocks.

Focusing on the national inflationary effects from shocks to CP ENSO types, we observed a significant positive effect on CPI inflation in India (0.5% by Q5 and Mexico (0.5% by Q2). For a number of European countries (including Austria, Belgium, Finland, France, Italy, Germany, Netherlands, Norway, Sweden), there was a positive response function (between 0.1 and 0.2%) that was statistically significant only after 2–3 yr. The USA, Canada, Japan, Korea and South Africa displayed a similar response profile to the European countries (between 0.1 and 0.2% effect on inflation). The Latin American countries in our sample did not display statistically significant effects. In contrast to the evaluation of CP effects, the analysis of EP ENSO types on national inflation rates generated insignificant results.

Global commodity prices are also affected by ENSO diversity. Shocks to CP ENSO types increased non-oil commodity prices; world real non-oil commodity prices increased by 1.5% by Q8, whilst real oil prices fell by approximately 1.5% by Q2. In contrast, shocks to EP ENSO types did not affect real non-oil commodity prices; the effect on oil prices was negative, reaching 1% by Q12.

Comparing our results to the existing literature, a good starting point are the results of Cashin et al. (2017), who also use quarterly data and the GVAR methodology. As noted in Section 1, they reported negative GDP effects on Australia, Brazil, Indonesia, Peru, the Philippines, and South Africa and positive effects on Argentina, Canada, China, Chile, Europe, Singapore, Thailand and the USA.<sup>22</sup> We found that positive or insignificant effects are the norm for CP ENSO and insignificant effects for EP ENSO. The major differences between CP and EP effects suggests that studies that fail to capture these differences may generate artefact results.

Cashin et al. (2017) reported inflationary effects for most countries. We also found that most of the 26 countries in our study had inflationary effects, although magnitudes and time profiles differed significantly between our study and that of Cashin et al. (2017). In general, looking at the significance bands in Fig. 7 of Cashin et al. (2017), many of the effects are not clearly identified. In our study, the significant CP effects were clearly identified at the 90% confidence level. Cashin et al. (2017) (Fig. 6) found that the magnitude of the real oil price increase was over 10%

by Q3 and real non-oil commodity prices increased by over 5% by Q3. In contrast, we found that by Q3, real non-oil commodity prices increased by 0.5% and real oil prices fell by 3% by Q3. These results are quite different. Although we also used the GVAR statistical framework, there are a number of differences that may be relevant. First, we used a 26-country model whilst they used a 21-economies/regions model of the global economy; since the aim of using GVAR is to capture heterogeneity in effects, it makes sense to model national heterogeneity where possible. Second, our sample periods differ. Cashin et al. (2017) used quarterly data for the period 1979(Q2)–2013(Q1) whilst we used quarterly data for the period 1960(Q1)–2019(Q4). The longer time period allowed us to observe more ENSO cycles, improving the reliability of the estimates. Finally, our study modelled the effects of ENSO diversity as captured by CP and EP ENSO measures. We experimented with a number of sensitivity tests, such as changing the trade weights linking the global economy, using nominal/real effective exchange rates, using data for quarter-on-quarter variations and 4-quarter changes, and found the magnitude and sign of global commodity price effects to be robust. The differences between our results and those of Cashin et al. (2017) suggest that ENSO diversity is important when analysing the effects of El Niño on the economy.

Comparing our results to studies using standard panel statistical methods is not directly possible, since the GVAR framework differs from standard panel econometrics, but this is a good opportunity to comment on these results in light of different methodologies. Smith & Ubilava (2017), Callahan & Mankin (2023), and Liu et al. (2023) each used panel distributed lag econometric models to identify the effect of the ENSO cycle on economic growth. These studies considered a large number of countries at an annual frequency over the period since ca. 1960. The focus of all 3 studies was on the output (GDP per capita) effects of the ENSO cycle. In general, they each found significant negative effects that persisted over a number of years. Callahan & Mankin (2023) found significant negative impacts that had persistent effects over a 5–10 yr horizon. Liu et al. (2023) estimated a panel distributed-lag for an unbalanced panel of annual GDP per capita data for the period 1960–2019 and found that the effect of the El Niño phase of the ENSO cycle lasted over a 3 yr period and built to large negative effects over the 3 yr; in contrast, the macroeconomic effects of the La Niña phase were not statistically significant. A similar result was reported by Smith & Ubilava (2017). All of these

<sup>22</sup>The time-profile of the effects also differs; for example, Cashin et al. (2017) reported significant effects on Europe within the first few quarters. We found that the effect only becomes significant after 2 yr.

studies share a number of features: they all used the panel methodology with annual data for a large set of countries;<sup>23</sup> hence, their results attempted to capture the mean response across many countries; second, they each employed a panel distributed lag model and made a case for not including conditioning variables. The idea of excluding conditioning variables relies on the 'over-controlling problem' noted by Dell et al. (2014), resulting from climate variables impacting on other control variables in an economic model. However, it is difficult to know whether dealing with the 'over-controlling problem' introduces omitted variable bias in such models.

Comparing the GVAR results and the standard panel method results, there are major differences in the results generated from the 2 approaches. In general, the output effects identified by GVAR for the 26 countries in our study suggest that positive or statistically insignificant effects are dominant. Where positive effects were identified, they were significant over a shorter time-profile than was reported in the distributed lag panel models. However, these 2 sets of results need not be inconsistent; although we included the larger economies and captured the global effects of the ENSO process, panel studies could be capturing the negative effect on a large number of smaller countries affected by the ENSO process that were not included in our study because of a lack of quarterly data.<sup>24</sup> At the same time, it is important to note that our selection of countries covers a large proportion of world GDP, suggesting that the positive effects also need to be noted in the overall effects of the ENSO cycle. Another area of attention could be the importance of conditioning variables. The GVAR model is premised on using conditioning variables to model the global economic effects of the ENSO process. Given the complexity of the economic interactions, it is sensible to evaluate the effects of conditioning variables using the distributed lag models reported above as a way of evaluating the sensitivity of the results to omitted variables.

Our study has allowed us to model the importance of ENSO diversity in economic analysis. At the same time, comparing our findings with other studies suggests many areas for further work to complete the picture of ENSO effects. We hope that our results en-

courage further research on ENSO diversity and its implications for economic effects. There is much work to be done to better understand the ENSO–economy relationship.

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<sup>23</sup>Using annual data allows us to include many more countries in any study of the post-war period

<sup>24</sup>The lack of quarterly data for many of the smaller economies creates an unavoidable selection bias in our study. Despite this, there are significant advantages to being able to focus on the quarterly data for the major economies.

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#### Appendix. Quarterly data

**Real GDP (1950–2019):** The data source is Monnet & Puy (2019). The quarterly real GDP was constructed using quarterly historical Industrial Production data from the IMF International Financial Statistics volumes as an indicator variable. This was combined with official annual real GDP series from the Penn World Tables. Temporal disaggregation methods were used to extend existing official quarterly GDP statistics in the past using the method of Chow & Lin (1971).

**Consumer prices (1950–2019):** The data source is Monnet & Puy (2019). Consumer prices were constructed by collecting data directly from older paper versions of the IMF International Financial Statistics using the ‘cost of living’ index. The digital version of the IFS has continued the series for the more recent period.

We used the quarterly index of consumer prices to construct 2 measures of CPI inflation: first we constructed the quarter-on-quarter inflation rate; second, we constructed the 4-quarter annual inflation rate retaining the quarterly structure of the data. The inflation rates we calculated follow a similar magnitude and time profile to the inflation data from the World Bank (A Global Database of Inflation, Ha et al. 2023) which begins in 1970.

**Real and nominal effective exchange rates:** The data are based on the work of Darvas (2012). We constructed the data as a monthly series that we aggregated to the quarterly frequency by averaging. Data are available for

the following countries: Argentina, Austria, Belgium, Brazil, Canada, Chile, Finland, France, Germany, India, Italy, Japan, Korea, Mexico, Netherlands, Norway, New Zealand, Philippines, South Africa, Spain, Sweden, Switzerland, Turkey, UK, USA.

**World commodity prices:** We used a number of indices from the monthly data series of the World Bank ‘Pink Sheet’ data (<https://www.worldbank.org/en/research/commodity-markets>).

The monthly data of oil prices, energy prices and non-energy commodity prices were aggregated to the quarterly frequency by averaging.

**Trade weights:** Trade weights were constructed using the IMF Trade flow data from IMF’s Direction of Trade series. We used the trade flow since ca. 1950 to construct weights that capture the significant changes in trade shares across time. We then selected weights for particular benchmarks (1950, 1960, 1980) to capture these temporal changes.

**ENSO measures:** SST anomalies in the Niño 3.4 region (5° N–5° S, 120–170° W), based on centered 30 yr base periods, are updated every 5 yr. [https://www.cpc.ncep.noaa.gov/products/analysis\\_monitoring/ensostuff/ONI\\_v5.php](https://www.cpc.ncep.noaa.gov/products/analysis_monitoring/ensostuff/ONI_v5.php)

**CP and EP ENSO measures:** The data we used are based on the work of Kao & Yu (2009) and Yu & Kim (2010). The data are monthly, which we aggregated to the quarterly frequency.