Identifying Terms-of-Trade Shocks with Foreign Weather: Implications for Monetary Policy*

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Abstract

How do changes in terms of trade (ToT) affect business cycles, and how should monetary policy respond? I identify exogenous ToT shocks for 48 economies from a rich set of weather shocks to their trading partners. I apply machine learning methods to map high-dimensional weather shocks into low-dimensional components that predict future ToT out of sample, while avoiding overfitting. Using panel local projections, I show that a shock that deteriorates ToT by 10% over one year is stagflationary: it raises consumer prices by 3% and reduces real GDP by 1.5% over a five-year horizon. Because the effects materialize with lags, the central bank can adopt a *preemptive* policy response, but it faces a tradeoff under floating exchange rates. Using a sufficient statistics approach that is robust to the Lucas critique, I find that a one-time monetary tightening of 46 bps can stabilize inflation while monetary easing of 20 bps can close the output gap created by the shock. Under a dual mandate, the optimal stance is inaction. (*JEL* E30, E52, E58, F14, F41)

Keywords: *Terms of Trade, Climate Shocks, Extreme Weather, Machine Learning, Principal Component Analysis, Local Projections, Monetary Policy*

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1 Introduction

The effects of terms-of-trade (ToT) shocks on domestic business cycles are not fully understood, yet their large effects on open economies force policymakers to monitor them closely.[1] Because this remains an open area of research, policy responses are typically *reactive*: authorities intervene only once ToT shocks have already manifested in inflation, output, or employment.[2]

While such an approach may be adequate when shocks arrive unexpectedly and cause immediate disruptions, some ToT shocks are *anticipated* in the sense that their upstream causes can be observed before their full macroeconomic effects materialize.[3] For example, severe frosts in Brazil in 2021 damaged coffee crops, and importers of coffee – including the United States – anticipated higher food prices as coffee futures spiked.[4] Numerous other extreme-temperature, drought, and flood episodes (among others) have affected commodity trade prices and have occasionally appeared in the headlines (see Figure 1). The timing gap between the initial shock and its eventual effect on domestic prices could give policymakers a timing advantage if they respond *preemptively* rather than purely *reactively*. This consideration is particularly relevant because both monetary and fiscal policy operate with implementation and transmission lags (Friedman, 1961; Fischer and Cooper, 1973; Christiano et al., 2005; Romer and Romer, 2010; Aruoba and Drechsel, 2024). Gaining clearer insights into the timing, causal effects, and severity of ToT shocks is therefore essential for designing policies that mitigate their impact. But the identification of their causal effects, requires ToT movements to be exogenous—my paper addresses this concern.

In this paper, I develop a novel method to identify plausibly exogenous ToT shocks by combining high-frequency, high-spatial-resolution weather data with bilateral trade flows. My method is based on the idea that weather shocks observed in foreign territories can potentially affect an economy's bargaining power on international trade (meaning, the terms of trade) for reasons that do not reflect systematic responses to domestic economic conditions. For example, an unanticipated increase in the frequency at which temperatures exceed 35°C in Germany, can potentially affect consumer prices in the United States if this weather anomaly causes severe trade disruptions. I use machine learning methods to map high-dimensional foreign weather anomalies observed in all trading partners' territories into

[1] ToT is the ratio of export prices on goods and services to import prices.

[2] Recent analyses from Hansen et al. (2023) and Cuba-Borda et al. (2025) are just a few examples where recent inflationary episodes have been examined through the lens of a terms-of-trade shock. An interested reader may also read related speeches by Lagarde (2023) and Dhingra and Page (2023).

[3] Oil supply surprises are the canonical case of shocks with rapid inflationary pass-through (see Blanchard and Gali (2007)).

[4] This episode appeared in Reuters coverage in July–August 2021.

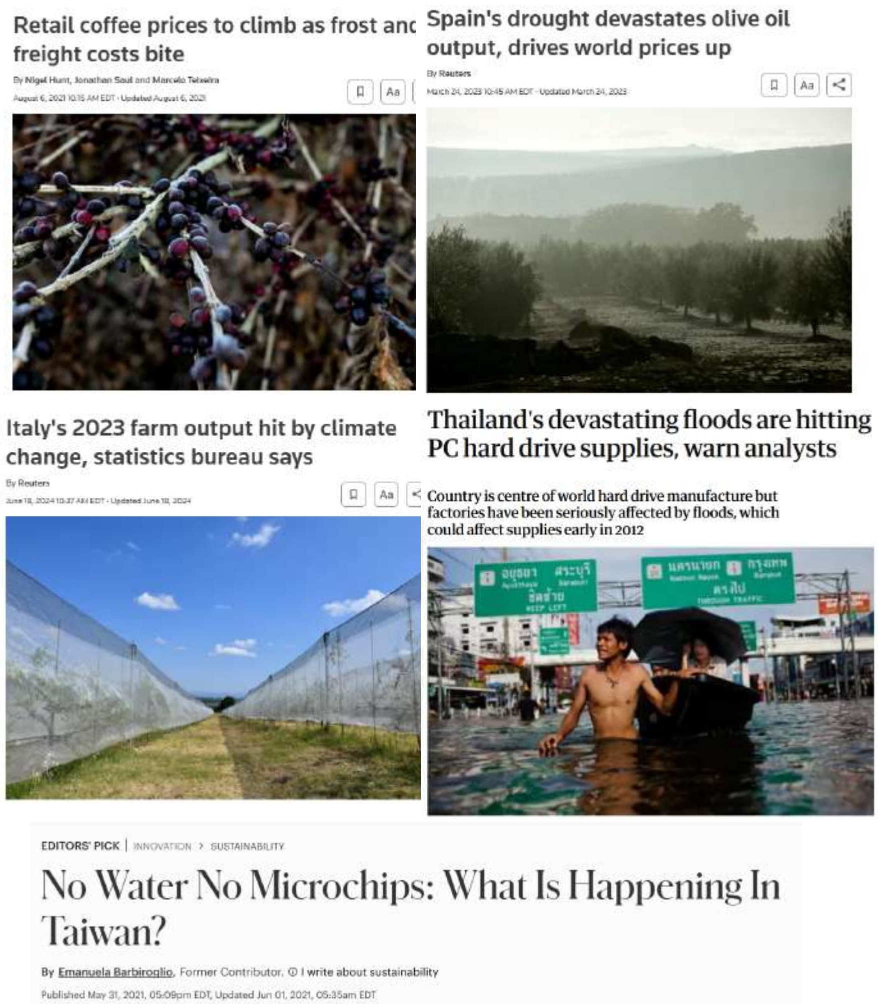

Figure 1: Examples of Weather-driven Terms-of-Trade shocks in the Headlines

economically meaningful low-dimensional components that (i) are orthogonal to domestic weather and (ii) predict future ToT out of sample. The weather anomalies considered in this study cover several dimensions of temperature- and precipitation-related events, including extreme temperatures, heavy rainfall, and drought episodes. Unanticipated changes in the frequency of these foreign natural events are usually temporary and regionally limited and can only affect the domestic economy through external accounts. Because they are not systematically tied to catastrophic events likely to trigger large-scale migration or capital-flow reallocation (e.g., earthquakes and volcanic eruptions), spillovers are most plausibly transmitted through the trade channel, supporting their interpretation as instruments for exogenous ToT fluctuations.

The country-level ToT shock data developed here enable quantification of the causal effects of ToT fluctuations, addressing a central limitation in the existing literature. Prevailing approaches often rely on global commodity prices and strong structural assumptions to isolate quasi-exogenous shifts in ToT, raising endogeneity concerns, especially for large open economies or major commodity producers who can influence global prices. By contrast, the weather-shock approach avoids this problem: no single economy can systematically generate global-scale high-frequency weather anomalies, at least over the mid-run. To my knowledge, this is the first paper to use an instrumental-variable approach to address this concern.[5]

I use these exogenous shocks to study the causal effects of ToT fluctuations on domestic business cycles with local projections in a panel of 48 countries from 1980 to 2019. While a large literature uses structural models and focuses on the causal effects of ToT shocks on output in small open economies, the reduced-form empirical study implemented here is also applicable to large open economies and it gives broader insights to their effects on key macroeconomic variables, their timing, and their magnitude. Adverse ToT shocks – defined as increases in import prices relative to export prices – are found to be both contractionary and inflationary in the medium run, but their spillover effects propagate with lags. Their stagflationary effects generate a policy trade-off for monetary authorities under floating exchange rates, analogous to the textbook supply-shock dilemma: they face a choice between stabilizing prices and closing the output gap. However, their lagged propagation allows for early intervention. This naturally raises the question: "*How should the monetary authorities respond?*"

This consideration motivates the third contribution of the paper: an empirical evaluation of the optimal monetary policy response to ToT shocks. I embed impulse response functions (IRFs) of key macroeconomic variables to ToT shocks, together with IRFs to monetary policy shocks, into a welfare loss function following a frontier methodology proposed by McKay and Wolf (2023). This framework enables a systematic evaluation of counterfactual policy responses without requiring a fully structural model. The idea is that, given sufficient knowledge of the dynamic effects of *unanticipated* monetary policy shocks, we can construct counterfactual policies that respond to an adverse ToT shock with a contemporaneous change of the policy rate.[6] Given stated monetary objectives, we can then estimate *optimal* policies that mitigate the dynamic effects of these shocks.

The results show that if monetary authorities prioritize price stability, the optimal response is immediate and relatively aggressive tightening: an adverse shock expected to cause a 10% deterioration in ToT one year ahead can be offset by raising the policy rate by about

[5] Contemporaneous work exploits weather shocks to study trade-side mechanisms but does not use them to instrument the terms of trade (Amodio et al. (2025) and Schenker and Osberghaus (2025)).

[6] As McKay and Wolf (2023) explain, these counterfactuals are robust to the Lucas critique if the IRFs are estimated on *unanticipated* shocks. The growing literature using high-frequency identification of monetary policy shocks makes such counterfactual evaluations feasible without strong structural assumptions.

46 basis points, neutralizing roughly 90% of its dynamic effects on consumer prices.[7] By contrast, if authorities prioritize closing the output gap, the optimal response is a moderate easing: a contemporaneous rate cut of about 20 basis points offsets roughly 70% of the shock's dynamic effects on production. Taken together, the results imply an inaction region: when authorities place relatively equal weights on price stability and output gap closure, policy interventions offsetting one objective amplify the other, rendering monetary intervention ineffective. In this case, the optimal stance is inaction.

Identification Strategy.—I draw on a rich dataset of climate variables from Akyapı et al. (2025), who construct 160 weather measures from high-frequency, high-spatial-resolution data covering 203 countries over 1979–2019. This allows me to capture weather anomalies from a wide range of climatic conditions beyond basic indicators such as average temperature or rainfall. I combine these data with lagged bilateral trade shares (BTS) to weight all foreign weather shocks across the globe by the country's trade exposure.[8] In particular, I use the UN Comtrade's annual bilateral trade flow data which covers over 200 economies from 1960 to compute BTS for each country-partner pair.

Because countries trade with many partners and each partner is exposed to many different weather shocks, the instrument set is high-dimensional relative to the available macroeconomic time series. I therefore apply standard principal component analysis (PCA) to extract orthogonal latent components that summarize systematic comovement in international weather shocks most relevant to the domestic economy. This procedure reduces dimensionality while preserving the economically meaningful variation needed for identification. Orthogonalizing to domestic weather ensures that the resulting components capture foreign shocks exogenous to domestic conditions, strengthening the exclusion restriction.

Not all common weather factors materially affect the ToT. I implement cross-validation to assess the out-of-sample predictive power of each component over future ToT and retain only those components with sufficient strength. This procedure yields a parsimonious set of predictors that are then mapped to future ToT growth to synthesize country-level instruments.

These instruments are valid if they satisfy two conditions. First, the *relevance* condition requires that the selected components explain variation in the terms of trade. This follows from clear economic channels: foreign weather shocks can disrupt supply chains and raise the cost of imported goods. These shocks can also shift foreign demand and thereby affect the prices of a country's exports. The relevance condition speaks to the motivation behind

[7] As I show on the main results, a roughly 2.5% deterioration of ToT on impact is expected to drop ToT by 10% one year ahead. The monetary authorities can intervene by monitoring the impact effect.

[8] Lagged BTS mitigate simultaneity and allow weights to reflect evolving trade patterns.

Figure 1.

Second, the *exogeneity* condition requires that the components are uncorrelated with fluctuations of domestic variables other than those sourced by the external accounts. By construction, the instruments are orthogonal to domestic weather shocks, which mitigates concerns that they capture spurious domestic effects. Moreover, these shocks operate primarily through trade flows rather than financial channels, reducing the risk that they proxy for shifts in investors' risk appetite.

Related Literature.—My work is related to three strands of the literature. The first is related to fluctuations of ToT. Early theoretical research has established ToT shocks as a critical driver of economic fluctuations in small open economies (SOE) (see Mendoza (1995), Kose (2002), Bidarkota and Crucini (2000)). Recent empirical studies are not conclusive on their severity. For example, Schmitt-Grohé and Uribe (2018) use a structural VAR model in poor and emerging countries and find that ToT account for less than 10% of fluctuations in aggregate output. This estimate is significantly smaller than the range between 30% and 50% initially predicted by the RBC models. Another study from Di Pace et al. (2025) finds ToT fluctuations mask underlying import and export price shocks. Taken together, their asymmetric effects explain about 40% of output variation.

The literature has primarily focused on SOEs for two reasons. The first is related to identification limitations. Most SOEs are considered too small to influence global prices. Existing measures of global commodity prices allow us to treat these prices as exogenous and study how price changes affect a SOE. One great example is a rich dataset constructed by Gruss and Kebhaj (2019) who combine international prices from 45 commodities with country-level trade data to construct ToT series.[9] This dataset expands the frontiers for more empirical research, but there are two caveats to keep in mind: First, a large open economy (LOE) can plausibly affect global prices. Second, even a SOE may affect global prices if they are large commodity producers. For example, a strike by copper miners in Chile, or a temporary cut of oil supply in Saudi Arabia could drive global commodity prices up. These are just a few examples where the exogeneity assumption of commodity-price-based ToT instruments can break down.

My work takes a different route to identify exogenous ToT shocks: it uses foreign weather shocks as instruments. The underlying assumption is that unanticipated weather shocks in foreign economies can only affect domestic business cycles through external accounts. I anticipate that foreign weather shocks can cause supply disruptions or shifts in foreign demand,

[9]An extensive literature has used international commodity prices to identify exogenous shifts in commodity prices and study their impact on domestic economy. For example, see Deaton et al. (1995), Chen and Rogoff (2003), Dehn (2000), Cashin et al. (2004), Spatafora and Tytell (2009), Aghion et al. (2010), Collier and Goderis (2012), and Ricci et al. (2013), among others.

all of which can affect the domestic country's bargaining power on international trade, but reverse causality does not hold. These foreign shocks would likely not affect domestic economic activity if it were not for trade openness. This provides a natural source of plausibly exogenous variation in ToT that can be exploited to study their macroeconomic consequences across a broad set of countries, without relying on strong structural assumptions.

The second reason why the literature has focused on SOEs is the conventional wisdom that these countries are heavily exposed to ToT fluctuations. Many SOEs and emerging economies are vulnerable to current account deficits and external debt, and their output is highly dependent on trade. The deterioration of ToT can cause severe financial distress and contraction in these economies. Advanced economies and LOEs, on the other hand, are perceived as more resilient to terms-of-trade fluctuations. In this study I show that ToT shocks affect advanced, high-income and LOEs as well.

The second strand of literature is related to the macroeconomic impact of weather shocks. The consensus is that adverse weather shocks depress economic activity. Climate shocks such as extreme heat and droughts curtail productivity and cause persistent slack and inflationary pressures (see Akyapı et al. (2025), Kim et al. (2025), Kahn et al. (2021), and Burke et al. (2015), among others). I borrow from this literature to build my *priors* on which weather events are more likely to cause macroeconomic effects. In my baseline model, I exploit the following multidimensional weather shocks: innovations in the frequency at which severe hot temperature, frost prevalence, extreme and severe droughts, high and extreme moisture, precipitation in very wet days and maximum extent of heavy precipitation occur within a country.[10]

Finally, my work is connected with a long and constantly evolving literature on the macroeconomic effects of monetary policy (see Bauer and Swanson (2023), Swanson (2023), Jarociński and Karadi (2020), Gertler and Karadi (2015), Nakamura and Steinsson (2014), and Romer and Romer (2004), among others). I borrow from this literature to get high-frequency exogenous monetary policy instruments to understand the dynamic effects of monetary policy shocks on key macroeconomic variables. This helps me to study how monetary policy should respond to ToT shocks.

2 Identification of Terms-of-Trade Shocks

In this section, I describe a new methodology to identify exogenous terms-of-trade (TOT) shocks.

[10] I get consistent results when testing the robustness of my results on alternative measures of weather events, or when focusing on less-frequent but more-extreme innovations.

Notation.——For what follows, let $\tilde{S}^i_{c,t}$ be a type-c weather shock observed in country i. I define a type-c weather shock as the innovation of a well measured climate variable, $c \in C$. For example, one such shock is the change in the frequency at which daily temperatures exceed 35°C. Another shock is the change in precipitation reported at very wet days. These weather anomalies are related to severe or extreme weather episodes and are not predicted by lagged climate variables. I present the set of weather variables C in Appendix A. I define the terms of trade in country i as the log transformation of the price level of exports relative to the price level of imports. That is:

$$x_{i,t} \equiv ln(P^x_{i,t}/P^m_{i,t}) \times 100$$

Then the cumulative ToT growth rate in percentage points over horizon h relative to time $t-1$ can be approximated as:

$$\tau^h_{i,t} \equiv \Delta x_{i,t+h:t-1} = x_{i,t+h} - x_{i,t-1} \tag{1}$$

2.1 Foreign Weather Shocks

Let country i trade with country j. Intuitively, unanticipated foreign weather shocks that are orthogonal to domestic ones (i.e., $\tilde{S}^j_{c,t} \perp \tilde{S}^i_{z,t} \;\; \forall j \neq i$ and $\forall c, z \in C$), can only affect the domestic economy through the external accounts. To understand if trade is an important transmission channel of these weather shocks, we could project future ToT on contemporaneous foreign weather shocks from all trading partners and use the fitted values to incorporate all these instruments into one synthetic variable. The regression would be as follows:

$$\tau^h_{i,t} = \alpha^h_i + \sum_j \sum_c \beta^h_{i,j,c} \times \tilde{S}^j_{c,t} + \epsilon^h_{i,t} \tag{2}$$

However, this approach would face an important limitation. Most countries trade with a large number of trading partners, and each trading partner could be affected by more than one type of weather episodes.[11] Accounting for all different weather shocks from all trading partners would weaken the model's statistical inference and risk overfitting, especially with limited time-series data.

To overcome this issue, I use unsupervised machine learning techniques to reduce the problem of dimensionality in foreign shocks. Specifically, for every country in the sample, I perform a principal component analysis (PCA) to identify common variations of weather

[11] For example, extremely low temperatures might affect consumers' demand and excess soil moisture might affect agriculture in the same country.

shocks originating from the country's trading partners. Take the USA as an example: every input variable of its PCA is a weather shock (e.g., an unanticipated change in the number of grid-days for which temperature exceeded $35°C$) observed in a foreign country (e.g., Mexico or Canada).[12]

Importantly, the principal components (PC) should capture economically meaningful common variations in weather shocks. By just including standardized shocks sourced from all trading partners without further manipulation, the PCA would attribute the same significance to partners who only trade a trivial share of their total trade with the domestic economy (e.g., less than 1 percent) and partners who trade a significant portion (e.g., more than 30 percent). Therefore, some pre-weighting is required before the variables enter the PCA. I measure country i's type-c foreign weighted shock from trading-partner country j as:

$$\tilde{S}^{i,j}_{c,t} = w^{i,j}_{y-1} \cdot \tilde{S}^{j}_{c,t} \qquad t \in y \tag{3}$$

where, $w^{i,j}_{y-1}$ captures the preceding year's bilateral trade share (BTS).[13] In essence,

$$w^{i,j}_{y} = \frac{X_{i,j,y} + X_{j,i,y}}{\sum_j (X_{i,j,y} + X_{j,i,y})} \tag{4}$$

here, $X_{i,j,y}$ denotes trading flows from country j to country i over the calendar year y. I use the preceding year's BTS to ensure my results are not driven by contemporaneous trade developments.[14] All climate shocks are standardized (within-country) so their units are interpretable in standard deviations away from mean. This is a standard procedure in PCA and ensures that the components do not just explain the variance observed in countries with more pronounced weather anomalies. Additionally, weighting these standardized series with bilateral trade shares allows the PCA to identify components that explain the portion of variance that is economically relevant for country i. Partners who only trade negligible

[12] If country i trades with a total of N_c countries, then a total of $N_c \times N_w$ variables enter the PCA, where N_w is the number of weather shocks.

[13] The decision to allow for aggregate bilateral trade flows (i.e., total *imports from* and *exports to* each country) instead of imports and exports on specific product categories (e.g., food and beverages), was made to keep the model as generic as possible. That way, the empirical identification approach does not restrict the trade channels through which spillover effects may occur. Understanding the aggregate impact on ToT is also essential for identification of the monetary policy response these shocks.

[14] Note that this practice is similar to an exercise from Bilal and Känzig (2024) who add up all foreign temperature shocks (weighted by BTS) to understand if economic spillovers explain the effects of global temperature shocks. The construction of foreign shocks in this work differs from their work in three ways. First, I allow for time-varying BTS because the composition of trade appears to have changed significantly for many countries since the 1960s. Second, I allow PCA to estimate common variations rather than adding up all shocks from all trading partners. Third, my analysis departs from temperature shocks and allows for a rich set of weather shocks.

values with the domestic country enter the PCA with variance that converges to zero. On the other hand, weather anomalies from the main trade partners will be assigned a weight based on their openness to trade with country i and will be preserved in the components.

In what follows, I derive the principal component analysis, followed by the orthogonalization of foreign shocks with respect to domestic shocks, and briefly describe the cross-validation procedure used to select informative principal components (the details are provided in Appendix A).

2.2 Dimensionality Reduction with Machine Learning

Principal Component Analysis.—For every country i, I stack all foreign weighted shocks into a vector:

$$\mathbf{X}_t^i = \left[\tilde{S}_{1,t}^{i,1}, \tilde{S}_{2,t}^{i,1}, \dots, \tilde{S}_{N_w,t}^{i,1}, \tilde{S}_{1,t}^{i,2}, \tilde{S}_{2,t}^{i,2}, \dots, \tilde{S}_{N_w,t}^{i,N}\right]'$$

where N is the total number of trading-partner countries and N_w is the number of weather variables. PCA reduces the dimensionality of $\mathbf{X}_t^i$ by estimating a series of components which successively inherit the maximum possible variance in the data. The principal components are estimated as:

$$\mathbf{P}_t^i = \mathbf{X}_t^i \mathbf{W}^i$$

where the loading matrix (i.e., eigenvectors) $\mathbf{W}^i$ satisfies:

$$\mathbf{C}^i = \mathbf{W}^i \mathbf{\Lambda} \mathbf{W}^{i,'}$$

Here, $\mathbf{\Lambda}$ is the diagonal matrix of the variances explained by each component (i.e., eigenvalues) and $\mathbf{C}^i$ is the covariance matrix:

$$\mathbf{C}^i = \frac{1}{T} \mathbf{X}_t^{i'} \mathbf{X}_t^i$$

where T is the number of periods.

Orthogonalization.—Let $\mathbf{P}_{k,t}^i$ be the k-th component of matrix $\mathbf{P}_t^i = \left[\mathbf{P}_{1,t}^i, \mathbf{P}_{2,t}^i, \dots, \mathbf{P}_{K,t}^i\right]$. Each component is regressed on country i's domestic weather shocks to avoid potential endogeneity issues. This endogeneity could arise if domestic weather shocks are linearly dependent with weather shocks observed in foreign territories. As domestic weather shocks can affect ToT through business cycle effects, the orthogonalization process ensures the instruments created from principal components affect the domestic economy through an international channel. The orthogonalization regression of the k-th component is:

$$\mathbf{P}_{k,t}^{i}=a+\sum_{\rho}^{N_w}b_\rho\tilde{S}_{\rho,t}^{i}+\tilde{\mathbf{P}}_{k,t}^{i}$$

where the residual components, $\tilde{\mathbf{P}}_{k,t}^{i}$, are orthogonal to contemporaneous domestic weather events. While the orthogonal components are included in the baseline methodology, my results are robust when I skip the orthogonalization process.

Cross Validation.—The PCA is useful to mitigate the dimensionality problem. However, the estimated scores, $\tilde{\mathbf{P}}_{k,t}^{i}$, do not necessarily explain fluctuations in terms of trade which is the main goal of this study. This can be illustrated with a simple example: Mexico remains one of the top trading partners of the US. Suppose Mexico is resilient to extreme temperatures and as a result, such shocks do not affect their trade with the US. From a US perspective, if any of the K principal components, say the first ($\tilde{\mathbf{P}}_{1,t}^{USA}$), is heavily weighted by temperature variations in Mexico, then this component, while it could explain a large fraction of total sample variance, may not have any predictive power over ToT. By treating all principal components as ToT instruments there is still risk of overfitting. Therefore, we need a sophisticated method to validate the components and retain a subset of powerful predictors of ToT.

I adopt an expanding-window cross-validation approach to select components that predict ToT growth out of sample. I start by removing components with small eigenvalues (i.e., components that explain less than 1% of the sample variance of foreign weather shocks). These components are more likely to introduce excess noise. I then assess each of the survived components based on their ability to predict ToT growth out of sample. If a component predicts out-of-sample ToT better than an autoregressive model can do, the component is characterized as "powerful" and is included in the set of instruments.

The expanding-window cross-validation process consists of the following steps. First, I split the sample into 10 folds and each fold is further divided into a *training* subsample and a *validation* subsample. The *training* window progressively expands as the sample unfolds, but there is no overlap across the *validation* windows. The *training* subsample is used to estimate the coefficients of $K+1$ models: an autoregressive model of ToT and an augmented model where a principal component, $k \in K$, is added in the autoregressive model. These coefficients are then used in the *validation* subsample to predict ToT growth out of sample. Then, I compute the mean absolute error (MAE) of the autoregressive model and the K augmented models in each fold, take their cross-fold medians and compare them to assess whether each component k outperforms the autoregressive model. A median MAE that falls below the median MAE of the autoregressive model characterizes the k-th component as a powerful predictor of ToT, and the component survives the cross-validation process. I detail the expanding-window cross-validation process in Appendix A.

The results are robust when the cross-validation process is substituted with less sophisticated methods. For example, I test the robustness of the synthetic ToT instruments by retaining a minimum number of components with the largest eigenvalues that explain at least 80% of sample variance. I also test the robustness of these instruments by including all components identified in PCA. The robustness checks are also shown in Appendix A.

2.3 Exogenous Terms-of-Trade Shocks

Having collected all economically-meaningful principal components that survived the cross-validation process, $\tilde{\mathbf{P}}^i_{k,t} \ \ \forall k \in \mathbb{K}_i$, I create country-level synthetic instruments of ToT where the weights of each component are directly determined by a country-level OLS regression of the form:

$$\tau^h_{i,t} = \hat{\alpha}^i + \sum_{k \in \mathbb{K}_i} \hat{\beta}^i_k \cdot \tilde{\mathbf{P}}^i_{k,t} + \varepsilon^h_{i,t} \tag{5}$$

This regression is similar to the one used in the cross-validation process except it exploits the entire sample and does not include the autoregressive component.[15] The regression of model (5) is the first stage of a two-stage least squares regression. As in the cross-validation process, I choose a horizon of 4 quarters as prices might adjust sluggishly to weather shocks.[16] The instrument is the fitted values:

$$\hat{\tau}^h_{i,t} = \sum_{k \in \mathbb{K}_i} \hat{\beta}^i_k \tilde{\mathbf{P}}^i_{k,t}$$

Given the dependent variable was expressed as the growth rate from $t-1$ to $t+4$, a 1-unit increase of the instrument is interepreted as the combination of weather shocks that are expected to cause ToT to grow by 1 percent, 4 quarters ahead. Finally, I normalize the instrument to make its series comparable across countries:

$$z_{i,t} = \frac{\hat{\tau}^h_{i,t} - mean(\hat{\tau}^h_{i,t})}{sd(\tau^h_{i,t})} \tag{6}$$

[15] In fact, the inclusion of control variables such as the autoregressive component did not change the coefficients of principal components significantly which comes as expected since the weather shocks are unexpected.

[16] Choosing a very short horizon, for example 1 quarter, is not ideal because weather shocks might only affect prices with a lag, and in this case would underestimate the dynamics of these shocks. On the other hand, choosing a very large horizon, for example 8 quarters, might introduce noise. A horizon of 1 year forward seems a fair period to anticipate any effects on ToT.

Notice that the denominator uses the standard deviation of the observed growth rate in the sample. A 1-unit increase of $z_{i,t}$ is now interpreted as an exogenous shock that induces ToT to grow by 1 standard deviation. The normalized series allows us to use the country-level ToT shocks in panel regressions and quantify their causal effect on key macroeconomic variables.

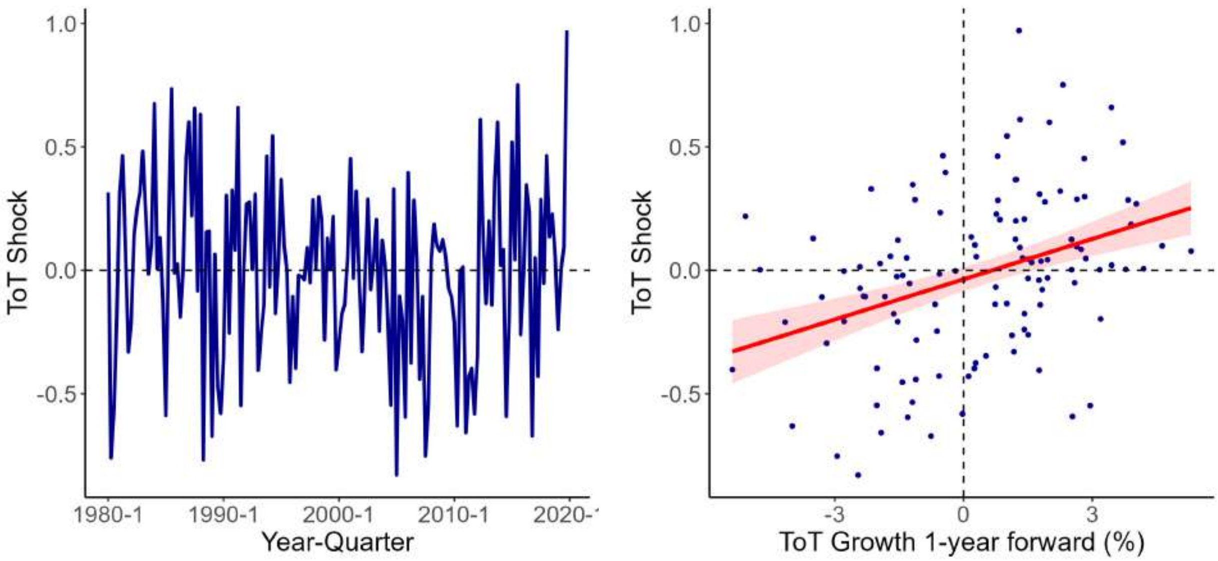

Figure 2: Terms-of-Trade Shocks in Germany

The left-hand side of the figure plots the time-series of terms-of-trade shocks in Germany over the entire sample period (1980-1999). The shock is scaled in standard deviations of a ToT growth rate from $t-1$ to $t+4$. The right-hand side of the figure shows the scatter plot of ToT shocks to realized ToT growth rate from $t-1$ to $t+4$. The **red**-colored straight line fits a simple OLS regression and the **red**-colored shaded region shows bootstrapped standard errors at the 90% confidence level (using 10,000 runs).

As an illustrative example, the left-hand side of Figure 2 shows the times of ToT shocks in Germany for the entire sample period from 1980 to 2019. The magnitude of the shock is usually small and occasionally exceeds one-half the standard deviation of a ToT growth rate. The scatter plot on the right-hand side shows a positive and statistically significant relationship between the shock and ex-post future ToT growth. Similar properties were found in ToT shocks from the remaining countries in the sample. I provide some descriptive statistics of terms of trade shocks in table B1.

2.4 Sanity Check

To understand how each foreign country contributes to the ToT shock, one can decompose Equation 6 to partner-j specific indices with:

$$z_{i,t}^{j} = \left(\sum_{k} \hat{\beta}_{k}^{i} \cdot \left(\sum_{c} \lambda_{k,c}^{j} \right) \right) \cdot \tilde{S}_{c,t}^{i,j} \tag{7}$$

where, $\lambda_{k,c}^{j} \subset \mathbf{W}^{i}$ are the weights of type-c weather shock from country j loaded into the k-th principal component. The covariance share is then:

$$share_i(j) = \left| \frac{cov(z_{i,t}, z_{i,t}^{j})}{var(z_{i,t})} \right| \cdot 100 \tag{8}$$

Figure 3 maps the covariance share of countries that traded with Germany over two different 20-year windows: from 1980 to 1999, and from 2000 to 2019, respectively. According to the map at the top panel, most of Germany's ToT instrument over the 1980-1999 window is explained by weather shocks observed in France, the Netherlands, and Italy and to a lesser extent by Switzerland, Belgium, and the United States (among others). The scatter plot on the right shows that countries with higher bilateral trade volumes are associated with economies

Moreover, by studying the covariance share over different windows, the map adjusted with top trading partners of that time confirming that the instrument captures very well the dynamic evolution of trade. This is seen, for instance, at the second panel of Figure 3. During the second half of the sample, Germany's exposure to foreign weather shocks has changed considerably. First, with the emergence of trade with China, weather shocks in China now affect Germany's terms of trade. Second, countries like Spain and Poland now affect Germany's trade (although to less extent). Third, Germany's exposure to some countries that remained top partners over the entire sample period has also changed. For example, its exposure to weather shocks in the US has increased, while its exposure from Italy has significantly dropped (presumably due to the larger trade diversification).

3 Data

Weather data.—I get weather data from Akyapı et al. (2025) (henceforth ABM). ABM exploit daily geospatial observations of temperature and precipitation around the globe and aggregate them across countries to construct a rich dataset of weather variables. Their main comparative advantage compared to other climate-related datasets is the fact that

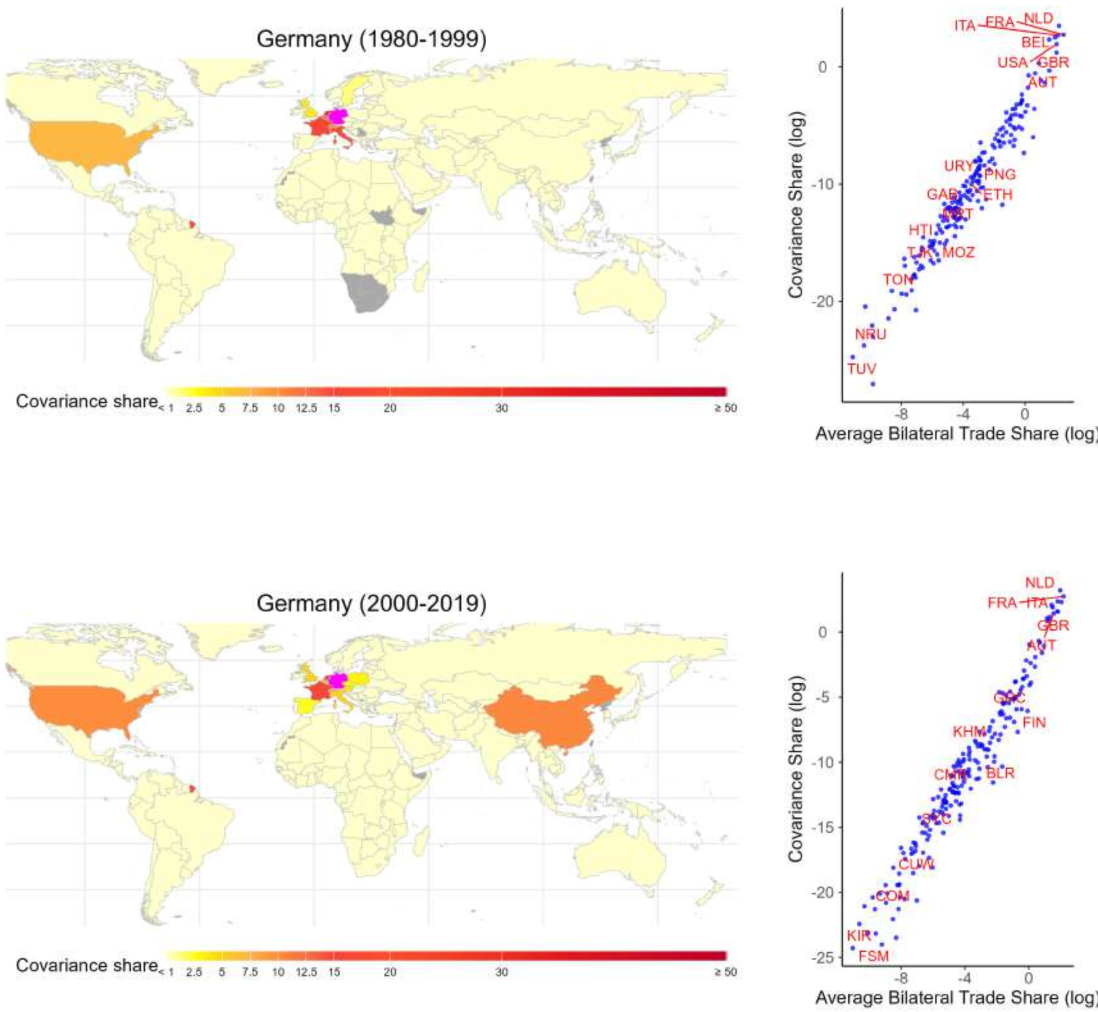

Figure 3: Instrument Decomposition by Country-origin in Germany

The figure maps the country-origin of terms-of-trade shocks in Germany attributed to foreign weather shocks over two 20-year windows (1980-1999 and 2000-2019). The heatmap colors countries from yellow to red in ascending order of covariance share. Yellow color indicates covariance share below 1%. Dark gray color indicates no trade data with this country. Magenta color identifies the domestic economy (in this figure, Germany). A scatter plot showing the positive relationship between the covariance share of equation (8) and the bilateral trade shares with Germany's trading partners during this window complements the maps on the right.

weather events that occur in specific regions (grids) and days of the year still survive in the aggregation process. For example, their frost prevalence variable captures the share of grid-days within a country where the average temperature was below 0°C. Their dataset includes a panel of 209 countries and a large set of variables. While their original dataset is at annual frequency, ABM provided monthly observations that start from January 1979 and end in December 2019. To match with ToT data, I aggregated their monthly series to quarterly using a simple average of monthly observations within a quarter.

Guided by the macro literature on weather and aggregate outcomes, I select a compact set of variables from ABM to span the main meteorological channels plausibly strong enough to operate through international prices and trade. These variables reflect temperature and precipitation extremes. Specifically, I retain six variables: the share of grid-days with maximum temperature above 35°C, the share of grid-days with average temperature below 0°C, the prevalence of *severe* and *extreme* drought, the prevalence of *high* and *extreme* moisture, precipitation on very-wet days, and heavy precipitation intensity (see Appendix A). The selected weather indices are then included in a small VAR model. I interpret the reduced-form residuals of these weather variables as unanticipated weather shocks and load them into the PCA.

Each chosen variable maps to well-documented macro effects in the literature. Extreme heat lowers aggregate productivity and output growth (Burke et al., 2015; Colacito et al., 2019; Kahn et al., 2021; Akyapı et al., 2025). Cold extremes and severe winter conditions also depress activity and affect fiscal aggregates (Bloesch and Gourio, 2015; Kahn et al., 2021; Akyapı et al., 2025). Drought episodes reduce GDP and can have persistent growth and price-stability consequences (Tintchev and Jaramillo, 2024; Ehlers et al., 2025; Akyapı et al., 2025). On the precipitation side, both excess moisture and the tails of the rainfall distribution matter for macro performance. Extreme daily rainfall and flood episodes dampen activity (Kotz et al., 2022; Ehlers et al., 2025).

Macroeconomic data.—The set of macroeconomic variables is standard in the literature. Most of macroeconomic variables are provided by the International Monetary Fund (IMF). This includes quarterly series from the following datasets: the National Economic Accounts, the Consumer Price Index, the Labor Statistics, and the Effective Exchange Rates dataset. The macroeconomic variables are terms-of-trade, real exports, real imports, real GDP, CPI, unemployment, real exchange rate, nominal exchange rate, real private consumption, real investment and net export-to-GDP ratio. I complement this data with the Central Bank Policy Rates dataset from the Bank of International Settlements (BIS) to get country-level policy rates. I provide details of the data in Appendix A. All data is seasonally adjusted.

Trade data.—My suggested methodology to identify economically-relevant foreign weather shocks through PCA requires some preweighting of the shock series. As I show in section 2, I scale foreign shocks with the preceding year's bilateral trade share (Equation (3)). To construct bilateral trade shares, I use annual bilateral export and import values for goods products from UN Comtrade. The series are available from 1962 to 2024. I provide details in the Appendix A.

When I merge the weather data with bilateral trade data, I get a sample of 194 countries. I impose an additional requirement that a country needs to report at least 80% of their total trade activity at UN Comtrade to be included in this study. If the maximum report ratio across periods falls below this threshold, the country is excluded.[17]

To construct the ToT shocks I require a country to have at least 20 years of available terms-of-trade data. There were 48 countries that satisfied this requirement. These are Albania, Australia, Austria, Belgium, Bulgaria, Bolivia, Brazil, Canada, Switzerland, Chile, Costa Rica, Cyprus, Czech Republic, Germany, Denmark, Spain, Estonia, Finland, France, United Kingdom, Greece, Croatia, Hungary, India, Ireland, Iceland, Israel, Italy, Japan, Korea, Lithuania, Luxembourg, Latvia, Mexico, Netherlands, Norway, New Zealand, Philippines, Poland, Portugal, Paraguay, Romania, Singapore, Slovakia, Slovenia, Sweden, Turkey, and the United States.

Monetary Policy Shock data.— To estimate counterfactual monetary policy responses, I use the high-frequency monetary policy instruments for the US from Bauer and Swanson (2023). Their data includes a series of orthogonalized shocks to macroeconomic announcements which is crucial because the counterfactual responses need to be unanticipated.

4 The Effects of ToT Shocks on the Economy

I estimate the dynamic effects of terms-of-trade shocks on domestic business cycles via local projections a la Jordà (2005) in panel data (Jordà and Taylor, 2016, 2025; Riera-Crichton et al., 2015; Cloyne et al., 2023). The model is:

$$y_{i,t+h} - y_{i,t-1} = \alpha_i^h + \alpha_t^h + \theta_y^h \cdot z_{i,t} + \sum_{\rho=1}^{4} \gamma_\rho^h \Delta y_{i,t-\rho} + \varepsilon_{i,t+h} \tag{9}$$

where the dependent variable is country i's growth rate of outcome (macro) variable y, h quarters after the shock relative to $t-1$, α_i^h denotes the country-fixed effects and α_t^h the time-fixed effects. The θ_y^h coefficient is the impulse response function and measures the cumulative causal effect of a 1-unit increase of z on y at horizon h. In the baseline results I control for 4 lags of the first-difference of variable y as it is standard with quarterly data.

[17]This is easy to verify as UN Comtrade reports total trade with the rest of the world which can be used as the denominator of the BTS. As a result, for each particular period, the sum of BTS may not necessarily add up to 1 if there are missing bilateral trade reports. Only three countries failed to meet this requirement: Saudi Arabia, Kuwait, and Iraq.

4.1 Aggregate Effects

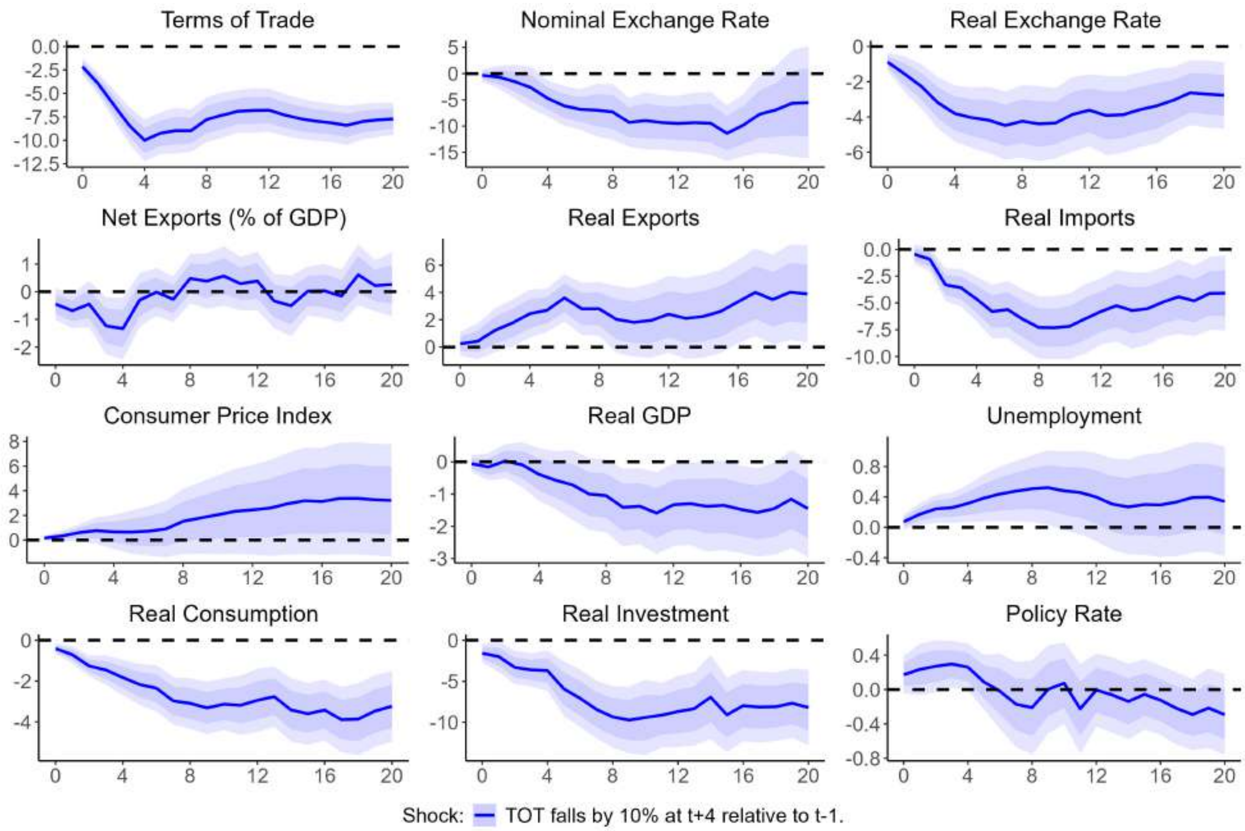

Figure 4: Impulse Responses to a Negative ToT Shock

The figure plots the IRF of 12 macroeconomic variables to a negative ToT shock that causes a 10% fall of ToT 1 year forward. The IRFs are estimated with the local projections model 9 in a panel of 48 countries over the period 1980-2019. All macro variables in the panel are expressed in $log \times 100$ format except for unemployment and the policy rates which enter as %. The confidence intervals are estimated with country-clustered standard errors at the 68% and 90% level.

Figure 4 shows the impulse responses of 12 key macroeconomic variables to a negative ToT shock. The shock is scaled to cause a 10% drop in ToT 1 year forward; this is equivalent to an impact effect of about 2.5%. The panel consists of all 48 countries for which the synthetic shock was generated. All macro variables in the panel are expressed in $log \times 100$ format except for unemployment and the policy rates which enter as percentage points. Table B4 in the Appendix reports the results for three different horizons: the impact effect, the cumulative effect at a 5-year horizon and the effect at peak/trough.

The macroeconomic consequences of ToT shocks have been studied extensively in SOE models, and the empirical findings presented here line up with textbook predictions. A negative ToT shock (which corresponds to a drop in export prices relative to import prices, or equivalently, a rise in import costs) is generally contractionary and inflationary for the domestic economy. This pattern is intuitive: a deterioration in ToT means the country earns less for its exports or pays more for imports, effectively losing its purchasing power. The result is a negative income effect (as seen with the fall in real GDP, consumption and investment) and imported inflation (as seen with the rise in consumer prices) via higher import prices and pass-through. The panel also shows a weakening currency (in real and nominal terms). The real depreciation reflects the economy's automatic adjustment to restore competitiveness by curbing import demand.

In numbers, the shock causes about 3% cumulative inflation over the five-year horizon. As I show later, this estimate is the result of heterogeneity among floating exchange rate systems (which exhibit inflationary effects) and fixed systems which experience deflation. The effects on real activity are also economically and statistically significant. Real GDP falls by around 1.5% about 2 years after the shock hits, and remains there over the mid-run. Unemployment gradually increases and reaches a peak about 2 years after the shock by about 0.5*pp*. Real consumption and real investment fall gradually and reach a trough at −3.8% and −9.7% respectively.

How likely is a 10% *fall in ToT?*—The magnitude of the shock is quite sizeable but feasible. Terms of trade are more volatile for small and emerging economies than they are for large and advanced economies. That is, the frequency at which a shock of this magnitude shows up, is significantly lower for advanced economies like the United States, and would signal a severe crisis episode. In Figure B2 I show that the minimum year-on-year ToT growth for half countries in the sample exceeded −10.68% and was below that level for the other half. For example, countries like Austria, Turkey, and the Philippines reach an all-time low growth rate of about −20%. In the more extreme, Chile shows a minimum −30%, India −42% and Norway −53%. The US reported a minimum of −16%.

4.2 Exchange Rate System Heterogeneity

The exchange rate plays a pivotal role in the transmission of ToT shocks. Under a flexible exchange rate system, a ToT deterioration is typically accompanied by a currency depreciation (nominal and real). This acts as a partial buffer: the weaker currency makes exports cheaper (boosting export volumes) and imports more expensive (further curtailing import volumes), which can help current account adjustment. Pioneering work by Broda (2004) compared the impact of terms-of-trade shocks under different exchange rate regimes. He found strong evidence for Friedman's shock-absorber hypothesis: countries with fixed systems suffer larger output declines when hit by a negative ToT shock, whereas those with flexible rates experience milder recessions thanks to swift currency depreciation.[18] In fixed-rate regimes, the real

[18] My analysis differs from studies who describe the long-run relationship between ToT and real exchange rate (see for example Cashin et al. (2004)). The IRFs presented here merely describe short- to mid-run

exchange rate adjustment is slow and occurs via deflation, which is painful for output. By contrast, floating regimes see an immediate nominal and real depreciation that helps redirect expenditure toward domestic goods.

Are these results supported with the identified shocks in this study? To answer this question, I adjust the panel local projections model to allow for heterogeneity of IRF across two different groups of countries: those under fixed and under floating exchange rates. The allocation of the countries into one of the two groups was made using the exchange rate regime classification data from Ilzetzki et al. (2019) and Ilzetzki et al. (2022).[19] The panel model is adjusted to:

$$y_{i,t+h} - y_{i,t-1} = \alpha_i^h + \alpha_t^h + \theta_y^{h,fxd} \cdot \mathbb{I}_{i,t}^{fxd} \cdot z_{i,t} + \theta_y^{h,flo} \cdot (1 - \mathbb{I}_{i,t}^{fxd}) \cdot z_{i,t} + \sum_{\rho=1}^{4} \gamma_\rho^h \Delta y_{i,t-\rho} + \varepsilon_{i,t+h} \quad (10)$$

where $\mathbb{I}_{i,t}^{fxd} = 1$ if country i was under a fixed exchange rate regime at time t, and 0 otherwise.[20] The results shown in Figure 5 indicate findings from Broda (2004) hold for the panel of 48 economies. Countries under a peg experience more pronounced recessions as observed with the fall in real GDP, consumption and investment. This group experiences steady deflation after the shock indicating a typical business cycle effect. Countries under floating rate respond with a nominal depreciation after the shock. Real output starts falling after about a year and it only turns significant two years after the shock hits. The recession is mild compared to the pegged countries.

Another dimension of adjustment is the trade balance. A negative ToT shock often causes a temporary deterioration in the net exports/GDP ratio, even if volumes adjust favorably. This is sometimes called the "income effect" dominating in the short run: export revenues fall (due to their relative lower prices) and import costs rise, so the trade balance can worsen immediately, even though the volume of exports rises and import volume falls. Over time, as the volume effects accumulate, the trade balance may improve back toward baseline or even reverse – consistent with what is seen in Figure 4. This pattern is consistent with a J-curve effect often discussed in international economics, except for the fact that the IRF of trade balance does not reveal a significant surplus in these results.

The domestic absorption components (consumption and investment) generally contract after an adverse ToT shock, as households and firms face a decline in real income. Previous

dynamic effects of ToT shocks.

[19] I used their coarse data and converted their monthly series to quarterly using end-of-quarter values. I grouped the hard and soft peg categories together as a *fixed* exchange regime and the intermediate and float as a *floating* exchange rate regime.

[20] Columns 2 and 3 of Table B3 show the number of periods for which a country is assigned under the *fixed* and *floating* system respectively.

studies focusing on emerging economies align with this: ToT windfalls (i.e., positive shocks) often fuel consumption booms, whereas ToT busts force painful import compression and investment cuts (Mendoza, 1995). My findings agree with these studies.

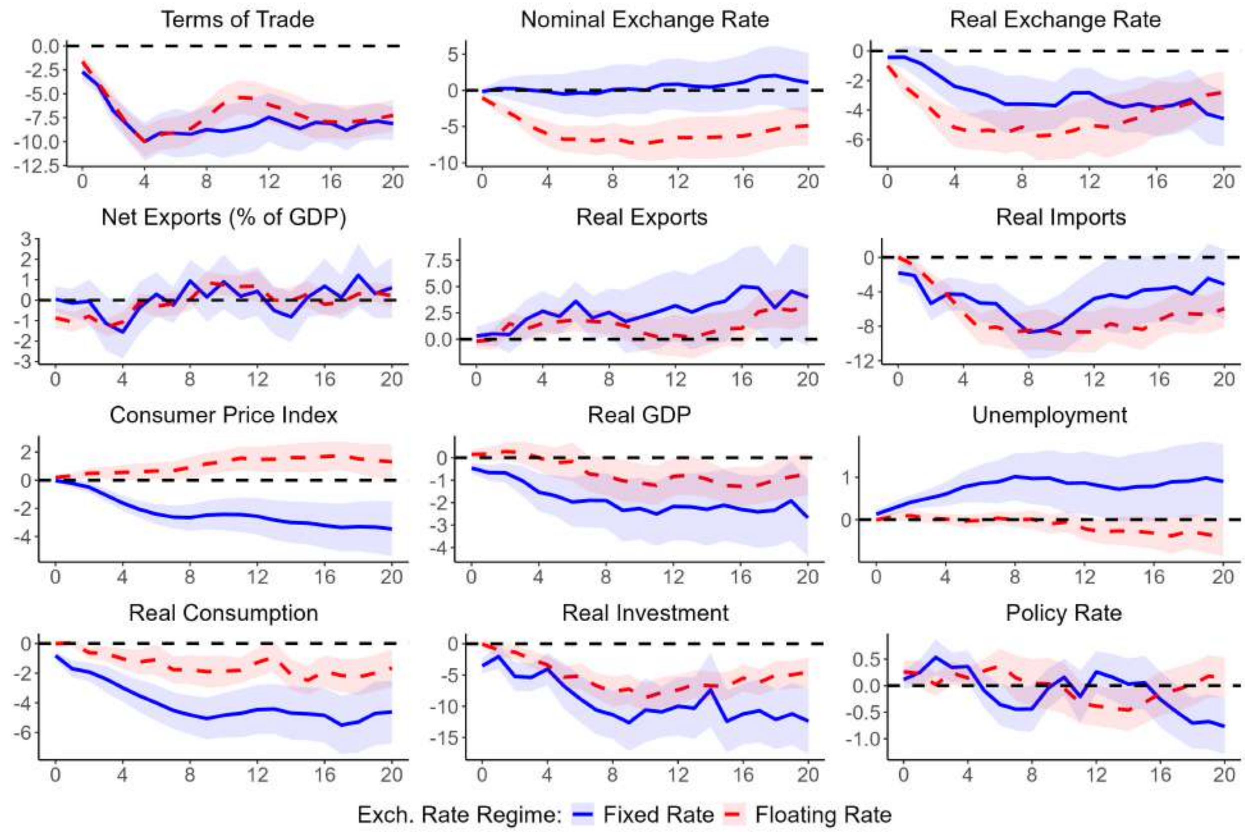

Figure 5: IRF to a Negative ToT Shock Under Different Exchange Rate Regimes

The figure plots the IRF of key macroeconomic variables to a negative ToT shock that causes a 10% fall of ToT 1 year forward. The IRFs are estimated for two groups of countries with the local projections model 10 in a panel of 48 countries over the period 1980-2019. All macro variables in the panel are expressed in $log \times 100$ format except for unemployment and the policy rates which enter as %. The confidence intervals are estimated with country-clustered standard errors at the 68% level.

Robustness.——I assess robustness along multiple dimensions (see details in Appendix A and a summary of results in Table A2). First, the results are not driven by extremes: trimming the top and bottom 1% of ToT shocks and of outcome variables leaves the estimates virtually unchanged. A leave-one-country-out jackknife confirms that no single economy drives the findings, and jackknife standard errors are close to baseline. Inference is stable across standard-error choices: country clustering, two-way clustering by country and time, and a wild-cluster bootstrap for small-N/T panels yield similar confidence intervals. Results are also robust when I include global controls (e.g., oil-price inflation) in place of time effects as a check.

Second, the identification steps are stable. Adding lags of ToT growth in the synthesis regression of Equation 5 leaves the country-level shocks essentially unchanged, and controlling for lagged ToT shocks in the panel local projections yields nearly identical responses. Including *all* principal components—rather than the set selected by cross-validated out-of-sample performance—does not alter conclusions, indicating that selection mainly improves signal-to-noise. Weighting choices further underscore the role of trade exposure in transmission. Using a two-year moving average of lagged bilateral trade shares (BTS) yields similar qualitative dynamics but weaker forecasts for CPI and real GDP, consistent with dilution of contemporaneous exposure. Omitting trade weights altogether sharply reduces predictive content: the unweighted instrument delivers inflation and activity responses that are small and statistically indistinguishable from zero, suggesting that weather shocks from marginal trading relationships add noise rather than signal.

Consistent with this narrative, local projections of sovereign spreads on ToT shocks show a delayed and comparatively small financial response. Partner composition matters quantitatively: restricting instruments to large partners (BTS$>$ 10%) strengthens inflation and output responses, while restricting to small partners (BTS$<$ 1%) attenuates them. Finally, augmenting the baseline weather set with rarer, more extreme events (e.g., days-grids above 40°C, and extreme droughts, among others) yields qualitatively similar and more pronounced dynamics.

5 Comparison with Different Measures of ToT Shocks

How do these weather-driven ToT shocks compare with other approaches seen in the literature? In this section I answer this question by examining two standard measures of ToT shocks: innovations of global commodity prices, and shocks from a structural VAR model.

Global Commodity Prices.—The first alternative consists of statistical innovations of a country-level commodity net export price index by Gruss and Kebhaj (2019) (henceforth GK). GK use global commodity prices to create a new dataset of commodity terms of trade. These prices are often considered exogenous, especially for small open economies, following the conventional wisdom that these countries are too small to influence global prices. It is a common approach in the literature to take the first differences of such indexes and study the effects of terms of trade. Since the commodity net export price index shows some persistency for most countries in the sample I use the residuals of an autoregressive model to proxy for unanticipated changes of ToT. The optimal number of lags is determined by the Akaiki criterion and is estimated for each country separately (see Table B5). The model is:

$$z_{i,t}^{(c)} = \Delta P_{i,t}^{(c)} - \sum_{p_i} \Delta P_{i,t-p_i}^{(c)} \tag{11}$$

where $\Delta P_{i,t}^{(c)}$ is the log difference ($\times 100$) of the Commodity Net Export Price Index for country i. I estimate these innovations for the period from 1980 to 2019 to make the series comparable with the weather-driven shocks.

Structural VAR.—The next measure is a structural shock identified by a SVAR model where terms of trade is ordered first in the Cholesky decomposition. The model resembles the work of Schmitt-Grohé and Uribe (2018) and imposes the same restrictions to identify structural shocks (see Equations (1)-(3) in their paper) but is not a precise copy of their model. I load the vector with terms of trade, net exports to GDP ratio, real GDP, real consumption, real investment, and the CPI index and use four lags of quarterly frequency for the period 1980-2019.[21] I denote these structural shocks as $z_{i,t}^{(s)}$ for consistency.

All three measures of ToT shocks are tested in the panel regression of Equation 9. Three countries were dropped out of the sample because their missing observations prevented identification of structural shocks. These are Albania, the Philippines, and Singapore.[22]

Figure 6 compares the dynamic effects of the three measures on key macro variables. All shocks are scaled to drop ToT by 10% four quarters after the shock. We can see that all shocks have persistent effects on terms of trade and the structural shock responds aggressively on impact while the weather-driven shock and global-price shock gradually fall until they reach a trough about 1 year after the shock. All three measures predict a real exchange rate depreciation on impact with the effect being relatively small under the weather-driven shock and steep under the structural shock. Some differences also appear on the quantities traded. The weather-driven shock predicts gradual but persistent increases of real exports which helps mitigate the adverse effect on trade deficit the relative price changes have caused. The two alternative measures predict sizeable increase in the quantity of exports during the first year, but the effects are mean reverting.

The differences are more apparent on inflation and economic activity. The weather-driven shock predicts gradual and persistent inflation and reconciles findings shown by the

[21] Schmitt-Grohé and Uribe (2018) use the real exchange rate instead of CPI and take per capita measures. I use CPI instead because some countries did not report real exchange rates and the model would generate shocks for a significantly smaller pool of countries. I use quarterly data instead of annual and do not impose any quadratic detrending, but instead let the lags control the trend.

[22] To make the series as comparable as possible, I drop any weather-driven shocks if global-price shocks are missing, and vice versa. I do not do the same for structural shocks because there were many missing observations. Therefore, structural shocks should be read with some caveats, but their dynamic effects seem compatible with what we anticipate from a SVAR model, which mitigates any concerns of false inference.

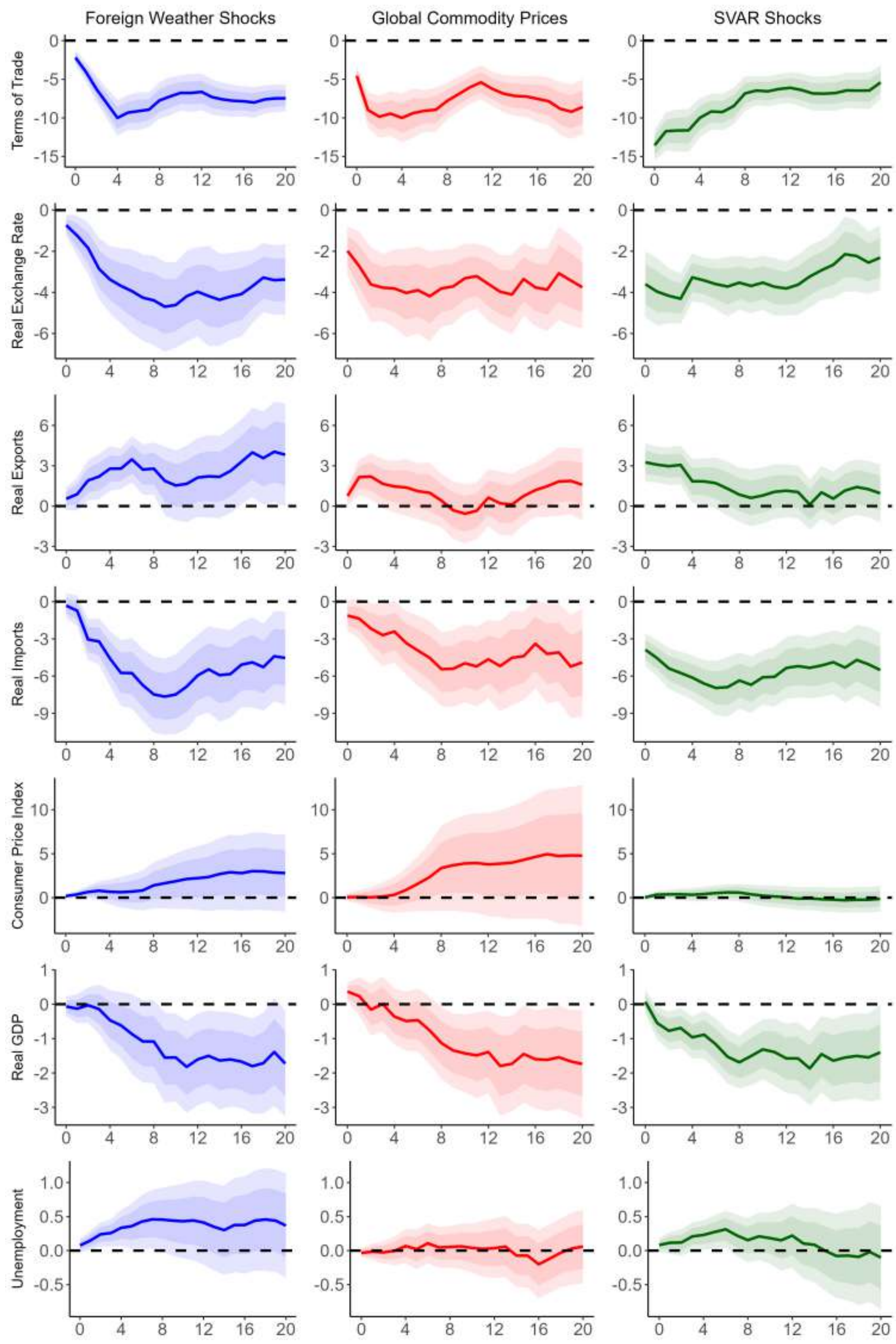

Figure 6: Comparison of Different Measures of Terms-of-Trade Shocks

The figure compares the dynamic effects of ToT shocks on key macro variables across different measures of ToT shocks: the foreign-weather-driven shocks (column 1), innovations of global commodity prices (column 2), and structural shocks from a SVAR model (column 3). All shocks are scaled to cause a 10% fall of ToT 1 year forward. The IRFs are estimated with a panel local projections model (see equation 9) for the period from 1980-2019. A pool of 45 countries is included in these regressions. Three economies were excluded because there was not available data to estimate their structural shocks; these are Albania, the Philippines, and Singapore. The panel has a total of 6,477 observations for weather-driven shocks and global commodity prices but 4,490 observations for the structural shocks. The confidence intervals are estimated with country-clustered standard errors at the 68% and 90% level.

remaining two measures. The structural shock predicts no inflation while the global-price shock predicts a more pronounced effect on prices. All three measures show similar effects on real GDP but some differences on unemployment. The weather-driven shock predicts unemployment to increase significantly and gradually after the shock contrary to the global-price shock which predicts no unemployment effects. The structural shock is in line with the weather-driven shock but the adverse effects on unemployment revert back sooner.

I continue by comparing the dynamic effects over different samples. I focus on differences between the weather-driven shock and commodity-price shock because I can compare these measures under the same observations without compromising the sample size. Figure 7 shows the effects on four variables: terms of trade, real exchange rate, consumer prices and real GDP. The first row plots (again) the entire pool of 48 economies to establish a baseline. Rows 2 and 3 illustrate the effects on *fixed* and *floating* systems, respectively. Interestingly, while floating-system economies exhibit the same dynamic effects under the two measures, the fixed-regime countries show different predictions. The most pronounced difference is observed on prices: the commodity-price shock predicts inflation (although statistically insignificant), while the weather-driven shock predicts deflation for these economies (which is significant and persistent). Also, real GDP falls more slowly under the weather-driven shock and the effect is only significant after 2 years. The commodity-price shock predicts recession that occurs faster. After a horizon of three years, the two measures agree on their predictions on real GDP.

Finally, I categorize the 48 countries into two groups: price *setters* and price *takers* depending on their ability to influence global prices. I define as price *setters* the G20 economies (for which I observe 13 of them) and I include Chile, Norway and New Zealand as they are large commodity producers. The remaining countries are grouped as price *takers*. Columns 4 and 5 of Table B3 list the countries into the two categories. Price setter countries exhibit similar dynamic effects on ToT and real exchange rates, but the commodity-price shock predicts faster and more pronounced inflation contrary to the weather-driven shock which predicts a smaller and more gradual one. Similarly, real GDP falls more gradually under the weather-driven shock.

Surprisingly, price-taker economies also exhibit significant differences. Price takers are expected to experience a pronounced, persistent and statistically significant inflation under the weather shock, while the commodity shock does not predict any inflationary effect. The effect on real GDP is noisy but insignificant under the commodity shock, while the weather shock predicts pronounced recession. The standard depreciation effect on real exchange rate does not show up under the commodity-price shock which might explain why this measure fails to predict significant effects on prices and economic activity. I interpret this finding as if this measure masks heterogeneity across price takers, rather than failure of the measure, but I leave this finding for future research.

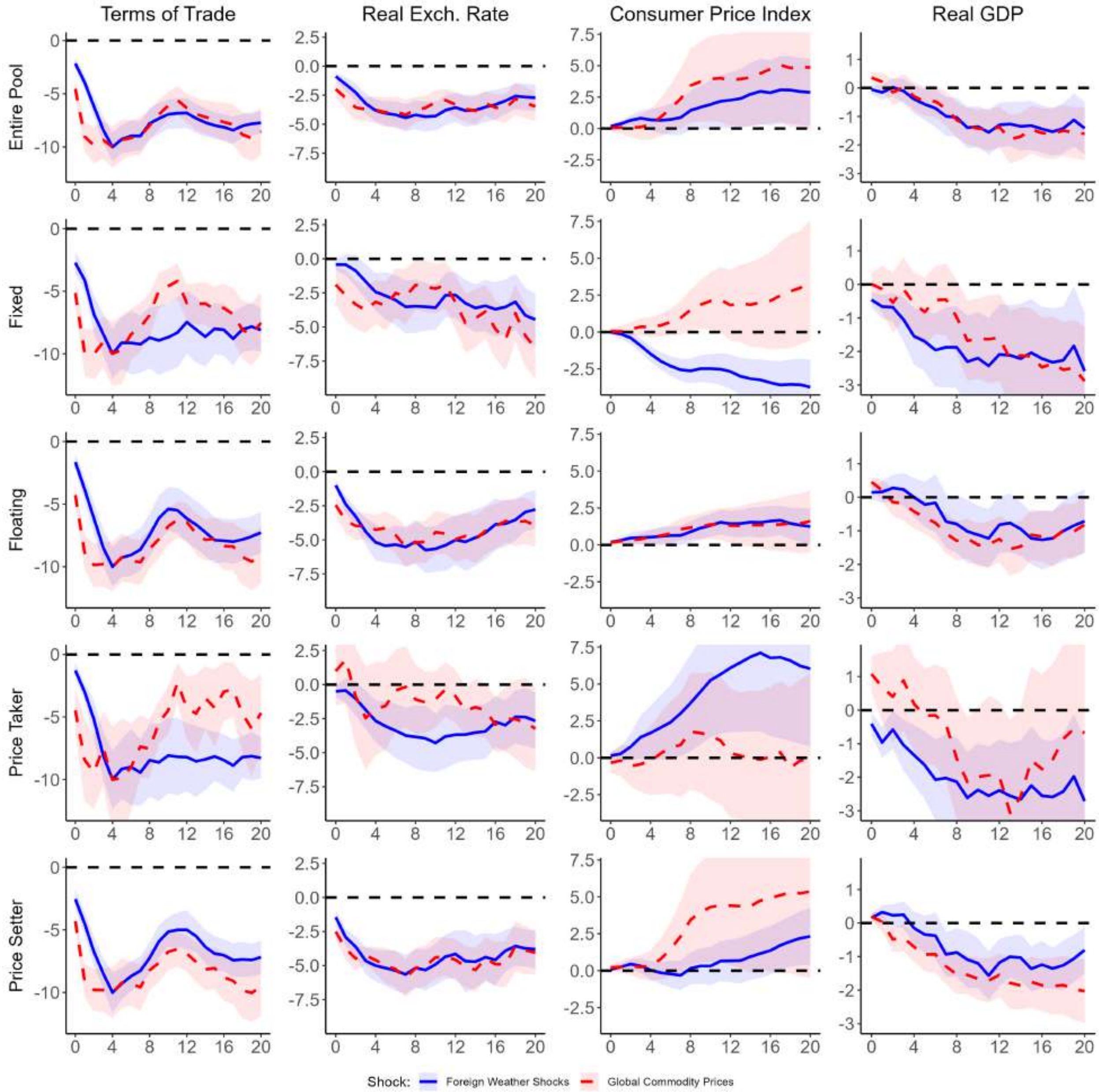

Figure 7: Comparison of Different Measures of Terms-of-Trade Shocks (Part II)

The figure plots the IRF of terms of trade (first column), real exchange rate (second column), consumer price index (first column), and real GDP (second column) to a negative ToT shock that causes a 10% fall of ToT 1 year forward. The IRFs are estimated with a panel local projections model with time- and country-fixed effects (see equation 9). The entire panel consists of 48 (16 price-setter and 32 price-taker) economies. An economy is grouped as a price setter if it is a G20 member country or a large commodity producer. An economy is grouped under the Fixed Exchange Rate System if it maintained a fixed peg or a narrow fixed band by the time it hit by the shock, and is a Floating system otherwise. The sample period of the ToT shocks data is 1980-2019, and the horizon goes up to 2024. The confidence intervals are estimated with country-clustered standard errors at the 68% level.

6 Optimal Monetary Policy Response to ToT Shocks

The main message of the previous sections is that ToT shocks matter for inflation and real economic activity. These findings complement evidence in the literature that emphasized the importance of ToT fluctuations in economic output, which was mainly based on structural models.

A natural question that arises is whether economies with monetary autonomy need to adjust their policies in anticipation of these inflationary effects. The idea is that if terms-of-trade shocks do not fully materialize on impact, but rather propagate with transmission lags, then their dynamic effects can be known well in advance, and a central bank might exploit this timing advantage to respond preemptively. This is particularly relevant because monetary policy transmits with lags. As shown already, negative ToT shocks drop ToT on impact and ToT keeps deteriorating one year forward. By anticipating their dynamic effects the monetary authorities can intervene before the tide arrives.

To study optimal policies I follow the seminal work of McKay and Wolf (2023) who use a linear structural model and show that under sufficient knowledge of the causal effects of contemporaneous and news shocks, one can estimate counterfactuals under alternative policy rules in a way that is robust to the Lucas critique. In addition, if a loss function is defined, we can derive optimal policy rules. Adams and Taipliadis (2025) implement this methodology in a SVAR model to estimate the optimal conventional and unconventional monetary policy responses when consumers' beliefs about future inflation are distorted.

The methodology requires three elements: knowledge of the dynamic effects of ToT shocks, knowledge of the dynamic effects of monetary policy shocks, and a welfare loss function. The first two are estimated by the IRFs to the corresponding shocks. The exogeneity condition of ToT shocks and monetary policy shocks is required, so the counterfactuals follow the Lucas program. The welfare loss function is only necessary to suggest *optimal* policies.[23]

IRF to ToT Shocks.— I use the IRFs of macro variables to a ToT shock on floating exchange rate regime countries as estimated from Equation 10.[24] Again, these responses are shown in Figure 5 and are scaled to reduce ToT by 10% four quarters after the shock hits. To enhance readability, I plot them again in Figure B1 (this time without the IRFs of the fixed regime countries). We can think of these IRFs as the counterfactual under no intervention by the central bank.

IRF to Monetary Policy Shocks.—One major limitation relates to the availability of plausibly exogenous monetary policy shocks across countries in the literature. I used a

[23] In this study, I define a loss function with monetary objectives. Therefore, any policy labeled as *optimal* is a policy that best fits these monetary objectives.

[24] I drop countries under fixed exchange rate regimes, because they lack monetary freedom.

series of high-frequency monetary policy shocks in the US from Bauer and Swanson (2023). Their identified shocks have two desirable properties: first, the high-frequency instrument is plausibly exogenous, and second, the series is orthogonalized to macroeconomic news, ensuring that the shocks are largely unanticipated.[25] I use a time-series local projection model to identify the IRFs to monetary policy shocks:

$$\Delta y_{t+h} = \alpha^h + \phi_y^h \cdot m_t + \mathbf{X}_t \cdot \gamma^h + \varepsilon_{t+h} \tag{12}$$

Here, m_t is the exogenous monetary policy shock and ϕ_y^h denotes the IRF of variable y to monetary policy shocks at horizon h. I control for two lags of the following year-on-year growth rates: CPI inflation, PPI inflation, real GDP, real investment and real consumption, and two lags of the following variables in levels: unemployment, policy rate, nominal exchange rate and the excess bond premium by Gilchrist and Zakrajšek (2012). I estimate the model of Equation 12 for the period 1989 - 2019.[26] Figure B2 in the Appendix shows the IRFs of the 12 macro variables to a contractionary monetary policy shock that raises the policy rate by 10 basis points on impact. Changes of the policy rate of this magnitude are frequent. For what follows, I rescale the shock to a 1 basis point contractionary policy to get a clear interpretation of the magnitude of policy response in basis points.

Welfare Loss Function.—Let θ_g^h and ϕ_g^h be the IRFs of output gap to terms-of-trade and monetary policy shocks respectively. Similarly, define θ_p^h and ϕ_p^h as the corresponding IRFs of the price level. Similar to Adams and Taipliadis (2025), I define a welfare loss function that takes as inputs the conditional variance of real GDP and CPI to shocks observed through a welfare horizon $\mathcal{H}$:

$$\mathcal{W}(\mathcal{H};\lambda) = \lambda V_g(\mathcal{H}) + (1-\lambda)V_p(\mathcal{H}) \tag{13}$$

where the weight parameter $\lambda \in [0,1]$ is determined by the objectives of the central bank. The monetary authorities may be committed to close the output gap, provide price stability, or may choose to monitor both objectives.[27] First, encode the IRFs in a single vector:

$$\theta^{h,flo} \equiv [\theta_g^{h,flo} \;\; \theta_p^{h,flo}]' \quad \text{and} \quad \phi^h \equiv [\phi_g^h \phi_p^h]' \tag{14}$$

[25] Specifically, I use their MPS_ORTH series from their updated monthly data and I aggregate them to quarterly data by taking the within-quarter sum.

[26] I exclude 1988 and the post pandemic era due to the presence of outliers. The inclusion of these dates did not produce a consistent IRF of CPI inflation.

[27] A more common monetary objective set by central banks is targeting the inflation rate. This welfare loss function does not imply that prices are set to remain stable under $\lambda = 0$, but rather it is the price changes induced by the shock that the central bank aims to revert to zero.

The vectors $\theta^{h,flo}$ and ϕ^h have dimensions $2\mathcal{H} \times 1$. Now, define a welfare matrix that assigns weights to the monetary objectives:

$$\mathbb{W} \equiv \begin{pmatrix} \lambda\mathbf{I} & \mathbf{0} \\ \mathbf{0} & (1-\lambda)\mathbf{I} \end{pmatrix} \tag{15}$$

Here, $\mathbf{I}$ and $\mathbf{0}$ are $\mathcal{H} \times \mathcal{H}$ identity and zero matrices. Assuming no intervention, the welfare loss when the economy is hit by a negative ToT shock is $\mathcal{W}(\psi = 0) = \theta^{h'}\mathbb{W}\theta^h$. Now, assume the central bank responds to the ToT shock by changing its target rate contemporaneously. The counterfactual IRF is now:

$$\tilde{\theta}^h(\psi; \lambda, \mathcal{H}) = \theta^{h,flo} + \phi^h \times \psi(\lambda, \mathcal{H}) \tag{16}$$

Notice how the combined shock is still unanticipated. The new welfare loss will be $\mathcal{W}(\psi; \lambda, \mathcal{H}) = \tilde{\theta}^{h'}\mathbb{W}\tilde{\theta}^h$. The minimization problem requires estimating $\hat{\psi}(\lambda, \mathcal{H})$ that minimizes the welfare loss function; this $\hat{\psi}$ is the optimal policy response.[28] Formally,

$$\min_{\psi(\lambda)} \left(\mathbb{W}^{\frac{1}{2}}\theta^h + \mathbb{W}^{\frac{1}{2}}\phi^h\psi\right)' \left(\mathbb{W}^{\frac{1}{2}}\theta^h + \mathbb{W}^{\frac{1}{2}}\phi^h\psi\right) \tag{17}$$

which translates to the following least squares problem:

$$\hat{\psi}(\lambda, \mathcal{H}) = \arg\min_{\psi(\lambda)} \mathcal{W}(\psi; \lambda, \mathcal{H}) = -(\phi^{h'}\mathbb{W}\phi^h)^{-1}\phi^{h'}\mathbb{W}\theta^h \tag{18}$$

and is solved by projecting $\mathbb{W}^{\frac{1}{2}}\theta^h$ onto $-\mathbb{W}^{\frac{1}{2}}\phi^h$.

The plot on the right-hand side of Figure 8 shows how the estimated suggested policies $\hat{\psi}$ change with different welfare weights $\lambda \in [0, 1]$. In the baseline results I choose a welfare horizon of 5 years. Columns 2-4 of Table B6 show these estimated coefficients. When the central bank prioritizes price stability over closing the output gap ($\lambda \to 0$), the optimal response is a contractionary policy. Let's consider the extreme case where price stability remains its single objective ($\lambda = 0$). The estimated coefficient $\psi = 46$ suggests that the central bank must raise its policy rate by 46 basis points to offset the inflationary effects of a shock that is anticipated to deteriorate ToT by 10% one year ahead. But is this policy effective? According to the left-hand side of Figure 8, when $\lambda = 0$, the R^2 of the regression model of Equation 18 reaches a peak at 90%. That is to say, the suggested policy can effectively absorb 90% of price fluctuations induced by the ToT shock.

[28] For what follows, I drop the parameters λ and $\mathcal{H}$ from the notation $\hat{\psi}$, but as shown earlier, the optimal policy changes for different welfare weights and welfare horizon.

On the other hand, the more the central bank prioritizes monitoring the output gap over price stability ($\lambda \to 1$), the more its optimal response leans towards expansionary policy. If the output gap remains its single objective ($\lambda = 1$), then the coefficient $\psi = -20$ suggests that the monetary authorities should drop the policy rate by 20 bps in response to the negative ToT shock. Again, the policy response can only partially offset the initial shock, but the high R^2 of 70% indicates that the policy response under this objective is also effective. The same is not true under the dual mandate: When $\lambda \in [0.37, 0.69]$ (that is the gray shaded area of the plot), then the optimal suggested policy is not effective at the 10% level of significance. Indeed, at this range, the R^2 is relatively low and does not exceed 8.6%. The result is intuitive: if the central bank equally cares about price stabilization and the output gap, the conventional response through policy rates is not effective because the negative ToT shock is contractionary and inflationary. Any effort to stabilize price stability, will destabilize output growth, and vice versa.

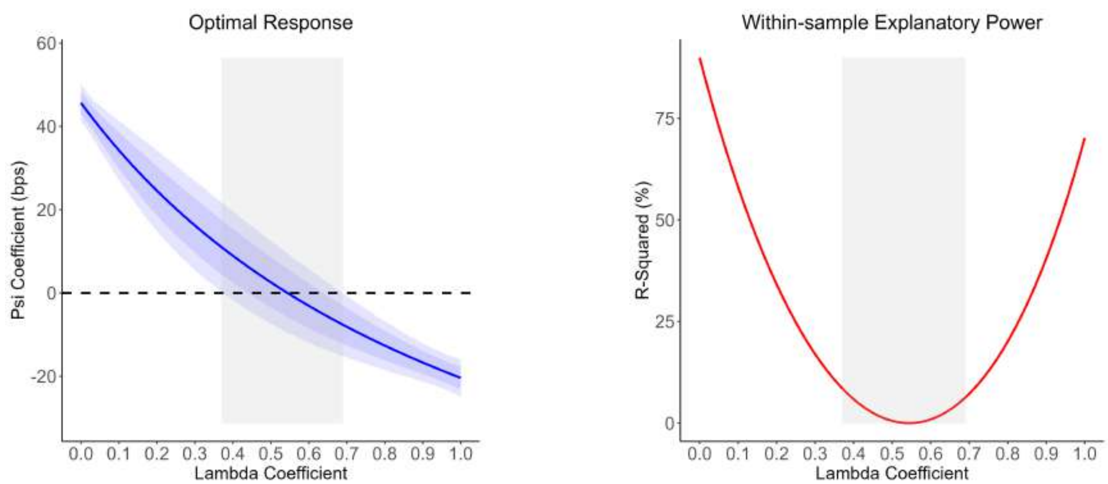

Figure 8: Optimal Policy Response Function

The plot on the left-hand side shows the estimated optimal response ψ (in basis points) as a function of the welfare weights λ. The confidence intervals are estimated with bootstrapped standard errors at the 68% and 90% level using 10,000 runs. The plot on the right-hand side shows the associated R^2 metrics of the OLS regressions used to estimate the ψ coefficients. The gray shaded area denotes the inaction area where intervention does not improve welfare loss. The model is estimated with welfare horizon $\mathcal{H} = 20$

Figure 9 shows how the dynamic effects of optimal monetary policy response vary depending on the central bank's monetary objectives. We can compare each counterfactual with the case when the central bank chooses to not intervene (see blue line). This is the case when the only shock that hits the economy remains the negative ToT shock. As seen above, if the central bank focuses on price stability, its optimal response is very effective. The magenta line shows that initially, CPI inflation increases slightly more than if it did not intervene. Inflation reaches a peak of 100 bps on the third quarter, but then falls towards zero. This comes with a cost: Price stabilization requires an initial increase in interest rates which lowers investment and consumption, and accelerates the recession caused by the ToT shock (as seen with the drop in output and increased unemployment).

On the opposite, the red line shows the optimal policy counterfactual when the output gap closure is the only objective. The initial drop of policy rates by 25 bps offsets almost completely the initial jump of policy rates by 26 bps caused by the ToT shock. Over the first one and a half years after the shock, real GDP increases but the growth rate is small and does not exceed 70 bps. Over the entire 5-year horizon, real GDP shows small fluctuation around zero growth rates. Notice how the intervention mitigates the drop in consumption and investment. The tradeoff is higher inflation as seen after the first year over the 5-year horizon.

The green line follows the dynamic effects of the ToT shock accompanied by the simultaneous optimal response when the central bank is equally concerned about the two objectives ($\lambda = 0.5$). This counterfactual produces IRFs that are almost identical to the non-intervention case. This comes as no surprise for two reasons: First, as can be seen in Figure 8, this case is located inside the inaction region (grey box). Second, the estimated optimal response under $\lambda = 0.5$ is an increase in policy rate of about 4 bps, which is economically insignificant.

Policy Response Elasticity of Welfare Loss.—The optimal response coefficients found earlier minimize the welfare loss function for given welfare weights and welfare horizon. In reality, monetary authorities might not always have sufficient policy space to target the optimal rate. In Figure 10 I show that under the price stability objective, the welfare loss drops below the loss that would be anticipated under no intervention for any positive response rate from 1 to 91 bps. Moreover, if the response falls between 16 and 76 bps, the welfare loss will be below 50% of the responding loss occurred under non-intervention. The same is not true under the dual mandate with equal welfare weights. Here, any welfare-loss minimization effort is not economically significant.[29] Finally, under the output gap closure objective, the welfare loss drops below the non-intervention case for any contractionary response from 1 to 40 bps. If the contractionary policy raises rates between 10 and 31 bps, then the welfare loss falls below 50% of the non-intervention case.

Policy response changes on different welfare horizons.—The central bank does not only choose the welfare weights, but also the horizon for which it tries to address its monetary objectives. Table B6 shows how the estimated optimal policies discussed above vary for different welfare horizons. I show that for a shorter welfare horizon (2.5 years) stabilizing

[29] When $\lambda = 0.5$, any response between 1 and 5 bps would drop the welfare loss below the non-intervention case, but this drop would be less than 1%.

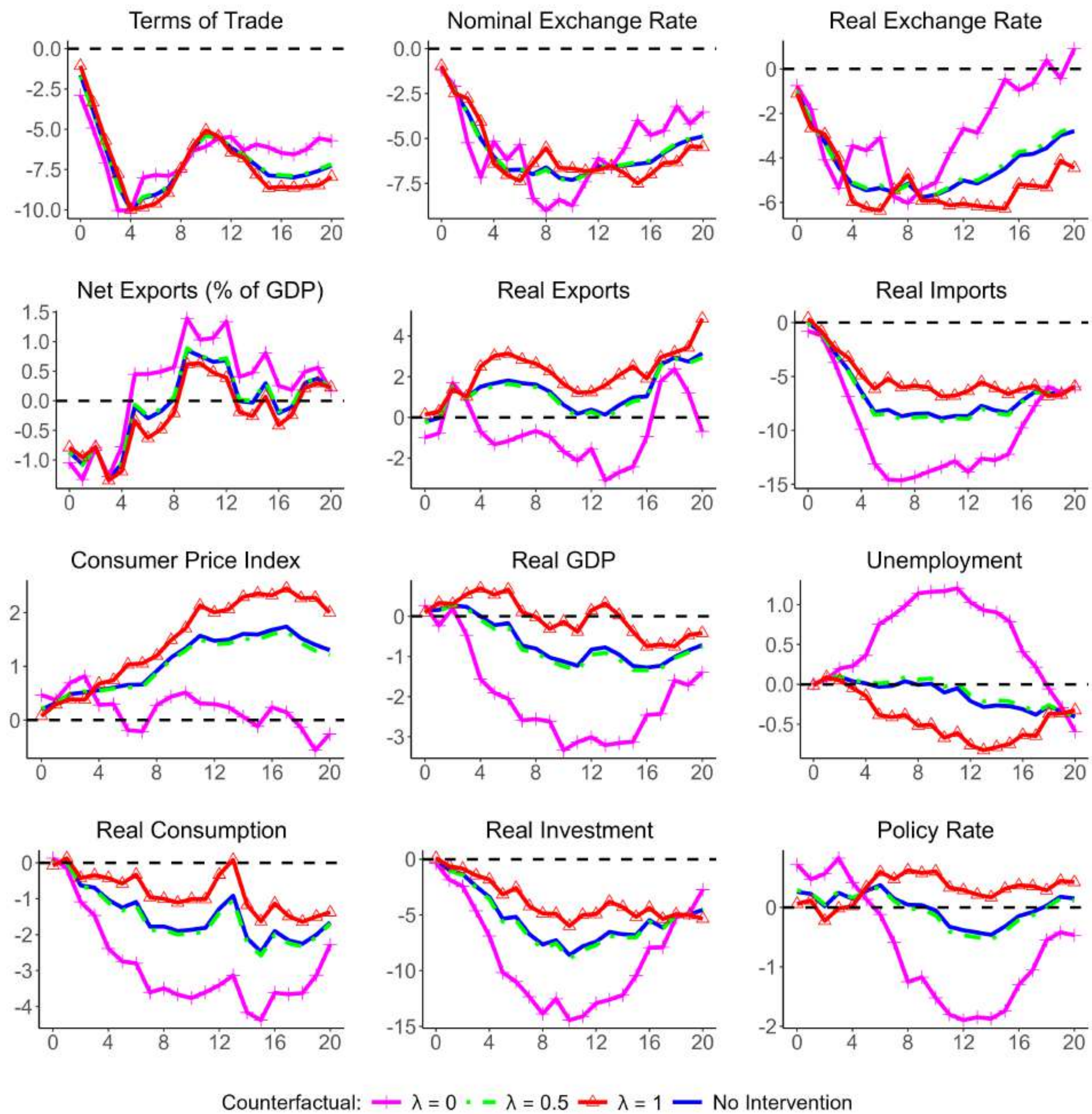

Figure 9: Counterfactual Optimal Responses under Different Welfare Weights

The plot shows the effect of counterfactual optimal policy responses on key macroeconomic variables for different welfare weights, λ. The blue line shows the dynamic effects under no response. The magenta line shows the impulse responses under optimal intervention when the central bank focuses on price stability ($\lambda = 0$). The red line shows the impulse responses under optimal intervention when the central bank focuses on closing the output gap ($\lambda = 1$). The green line shows the impulse responses under optimal intervention when the central bank equally cares about addressing the two objectives ($\lambda = 0.5$). The model is estimated with welfare horizon $\mathcal{H} = 20$.

prices would require a 48 bps contractionary policy while closing the output gap would suggest a 14 bps expansionary policy. When the criterion is extended for a longer welfare horizon (7.5 years) price stability requires a 22 bps contractionary policy while closing the

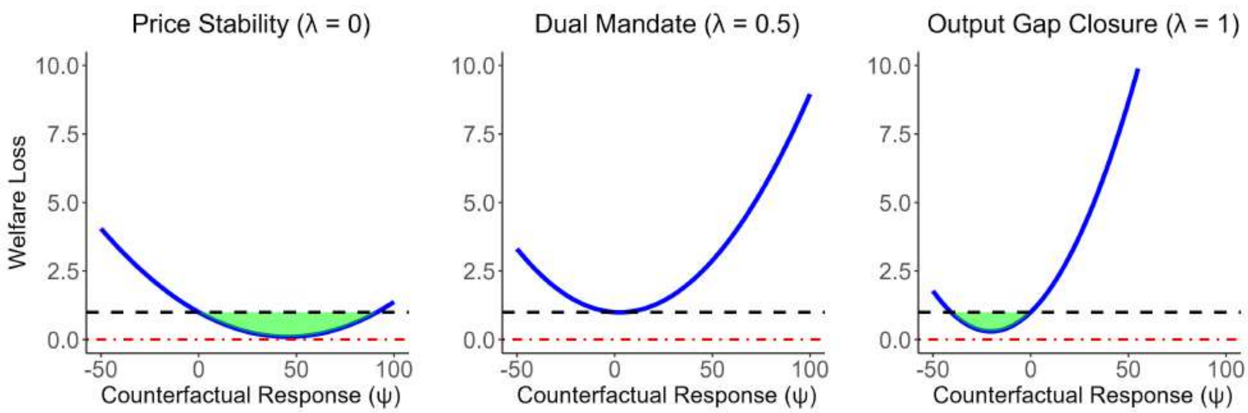

Figure 10: Policy Response Elasticity of Welfare Loss

The three plots show the welfare loss for a range of counterfactual policy responses from -50 to +100 bps. The plot on the LHS shows the welfare loss function when $\lambda = 0$. The plot in the middle shows the welfare loss function when $\lambda = 0.5$. The plot on the RHS shows the welfare loss function when $\lambda = 1$. The welfare loss under non-intervention ($\psi = 0$) is scaled to 1 on all three plots (dashed line). The green shaded areas show the region of policy responses under which the welfare loss falls below the loss under non-intervention. The model is estimated with welfare horizon $\mathcal{H} = 20$. The policy response becomes more effective as the welfare loss converges to 0 (red dash-dot line).

output gap calls for about 16 bps expansionary policy. Looking ahead at longer horizons makes the policy response less effective, as evidenced by the lower R-squared (about 33% and 24% respectively). This is expected as uncertainty increases over longer horizons.

Promoting Price Stability.—Let's now focus on one of the two objectives at a time. Figure 11 shows the counterfactual IRFs to different policy rules. I calibrate the welfare weight $\lambda = 0$ such as the central bank focuses on promoting price stability. To establish a baseline, I plot again the IRFs under no intervention (blue line) and under optimal intervention (magenta line). Let's suppose that the central bank deviates from the optimal policy, and adopts a non-optimal response. This is equivalent to changing the counterfactual IRFs of Equation 16 to any $\psi \neq \hat{\psi}$. For example, the green line responds to an overresponse that is twice the optimal rate. This response would cause deflation in the mid-run and a more prolonged recession, as evidenced by the deeper fall in real GDP and the steeper increase in unemployment.

On the contrary, the red line shows a counterfactual where the central bank adopts an expansionary policy of the same magnitude in absolute terms as the optimal policy indicates. Again, while an expansionary response would be desirable under the output gap objective, it contradicts the price stability objective which is assumed here. An expansionary monetary policy at the time when the economy is hit by a negative ToT shock would expand the economy by raising consumption, investment and real GDP and lower unemployment, but would amplify inflationary pressures. Under this rule, the CPI inflation is expected to double over the 5-year horizon compared to the non-intervention policy.

Narrowing the Output Gap.—Figure B3 in the Appendix draws equivalent counterfactuals

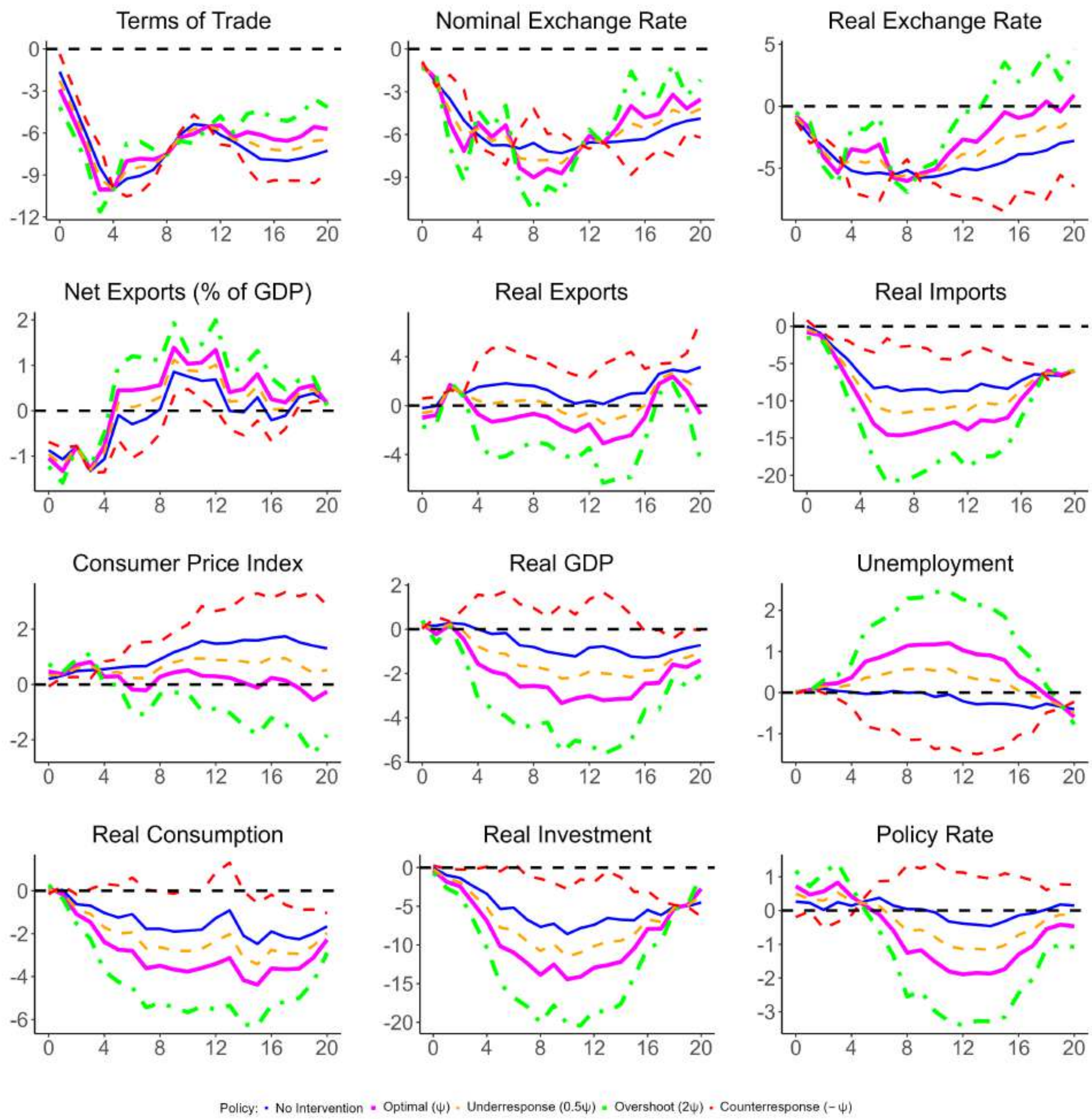

Figure 11: Counterfactual Impulse Responses to Different Policy Rules ($\lambda = 0$)

The plot shows the impulse responses of counterfactual policies on key macroeconomic variables. The model is estimated with $\lambda = 0$ and $\mathcal{H} = 20$. The blue thin solid line shows the dynamic effects under no response ($\psi = 0$). The magenta thick solid line shows the impulse responses under optimal intervention ($\psi = \hat{\psi}$). The red dashed line shows the impulse responses when the central bank adopts a policy on the opposite direction of the optimal ($\psi = -\hat{\psi}$). The green dotdash line shows the impulse responses when the central bank overresponds twice as much indicated by the optimal policy ($\psi = 2\hat{\psi}$). The orange dashed line shows the impulse responses when the central bank underesponds with half as much indicated by the optimal policy ($\psi = 0.5\hat{\psi}$).

when $\lambda = 1$. The results somewhat mirror those of Figure 11. When the central bank focuses completely on narrowing the output gap, then an overresponse not only closes the negative output gap, but also accelerates growth. Once again, this is paid for with higher inflation over the 5-year horizon. On the other hand, a counterresponse to the optimal policy partially stabilizes prices but amplifies the contractionary effects.

7 Conclusion

In this paper, I construct country-level exogenous terms-of-trade (ToT) shocks by combining high-dimensional foreign weather shocks with bilateral trade weights and extracting low-dimensional components that predict future ToT growth out of sample. This design supports causal inference on ToT fluctuations using reduced-form methods that do not rely on strong structural assumptions.

Using a quarterly panel of 48 economies over 1980–2019, I show that adverse ToT shocks are typically contractionary and inflationary at medium horizons, with economically significant and persistent effects. Responses differ by exchange-rate regime: countries with fixed (or tightly managed) exchange rates experience deeper and more prolonged output losses with deflation, whereas floaters face milder output declines but clear inflationary pass-through. These patterns are consistent with open-economy models in which flexible rates act as shock absorbers while pegs transmit shocks via domestic demand compression rather than relative-price adjustment. My work highlights two interesting findings. First, the costs of ToT disturbances are not confined to small open economies (as has been extensively studied). Large open economies and large commodity producers are also affected by ToT shocks, though to less extent than pure "price taker" economies. Second, the spillover effects of ToT shocks propagate into the domestic economy with significant lags. These lagged effects allow authorities to monitor ToT shocks and intervene accordingly.

Focusing on economies under floating exchange rates (which are more likely to preserve their monetary autonomy), I quantify counterfactual one-time monetary policy responses on impact of ToT shocks, and find most of the effects of the latter can be neutralized under a single monetary objective. Reverting prices to pre-shock levels requires aggressive tightening, while closing the output gap created by the ToT shock calls for mild expansionary policy. Under dual objectives, any intervention that stabilizes one margin tends to amplify the other, generating an inaction region in which non-intervention is optimal.

Beyond the findings presented here, the exogenous ToT shocks developed in this study enable several avenues for future research, some of which I list here: First, we can use the IRFs as empirical targets to discipline open-economy DSGE models. Second, we can study how trade-policy frictions – such as export bans or tariff changes – reshape transmission. Third, we can evaluate whether climate adaptation and risk-transfer tools attenuate ToT pass-through over time. Beyond academic applications, the shocks can inform macro-prudential stress-testing by supplying exogenous ToT scenarios with empirically grounded macro paths and policy overlays.

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Appendix A

A.1 Expanding-Window Cross-Validation Process

I adopt an expanding-window cross-validation approach to select components from the PCA that predict ToT growth out of sample.[30] I start by removing components that explain less than 1% of the sample variance of foreign weather shocks because these components are more likely to introduce excess noise in the data. I then assess each of the survived components based on their ability to predict ToT growth out of sample. If a component predicts out-of-sample ToT better than an autoregressive model can do, the component is characterized as "powerful" and is included in the set of instruments. The cross-validation process is as follows.

First, I split the sample into 10 folds; these are:

$$[\underbrace{1980-1998}_{T_1} \mid \underbrace{2000-2001}_{V_1}],\ [\underbrace{1980-2000}_{T_2} \mid \underbrace{2002-2003}_{V_2}], \ldots, [\underbrace{1980-2016}_{T_{10}} \mid \underbrace{2018-2019}_{V_{10}}]$$

where T_f and V_f are the training and validation samples of the f-th fold respectively.

For each country, i, and each fold, f, I use the training sample to run $K+1$ regressions: a baseline autoregressive model–where ToT growth is regressed to its own lags–and K regressions where each of the k components (alone) augments the baseline regression:

$$\begin{aligned} \tau_{i,t}^h &= \alpha_f^0 + \Sigma_{\rho=1}^4 \beta_{f,\rho}^0 \tau_{i,t-\rho} + \epsilon_{f,i,t}^0 \quad t \in T_f \\ \tau_{i,t}^h &= \alpha_f^k + \Sigma_{\rho=1}^4 \beta_{f,\rho}^k \tau_{i,t-\rho} + \gamma_f^k \tilde{\mathbf{P}}_{k,t}^i + \epsilon_{f,i,t}^k \quad t \in T_f \\ & \qquad \forall k \in \{1, 2, ..., K\} \end{aligned} \tag{A.1}$$

where $\tau_{i,t-\rho} = x_{i,t-\rho} - x_{i,t-\rho-1}$. In these regressions I choose a horizon of $h = 4$ quarters to allow enough time for weather shocks to propagate. I use four lags on the autoregressive model because that was the median cross-country optimal lag suggested by the Akaiki information criterion (AIC). I then use the coefficients from the $K+1$ regressions to predict out-of-sample ToT growth in the validation period of the same fold. I denote the predicted values as $\hat{\tau}_{i,t}^{h,(0)}$ and $\hat{\tau}_{i,t}^{h,(k)}$ $\forall k \in \{1, 2, ..., K\}$ for $t \in V_f$.[31] With these predicted values, I compute the mean

[30] I do not use supervised machine learning methods (e.g., LASSO, or Ridge regression) to identify significant predictors of ToT for two reasons. First, the penalty parameters tend to drop out pronounced weather shocks from top trading partners. That mainly happens because most ToT fluctuations occur for various reasons beyond weather events (e.g., trade policies, business cycles in foreign economies, and wars, among others). Second, these methods are likely to drop similar weather shocks observed from different trading partners even if both partners are influential to domestic business cycles.

[31] Notice that the gap between samples T_f and V_f was left intentionally as the left-hand side of the

absolute error of the $K+1$ models over the validation sample, V_f. By iterating over all folds, I compute the cross-fold median MAE and collect all principal components that achieved smaller median MAE than the baseline model. That is:

$$\mathbb{K}_i = \left\{k \in \{1, 2, ..., K\} : MAE_i^k < MAE_i^0\right\} \tag{A.2}$$

where $\mathbb{K}_i$ is the set of principal components of foreign weather shocks that are powerful and economically meaningful for country i, and MAE_i^k and MAE_i^0 are the cross-fold median MAE of the regression models k and baseline respectively. There are a few notes about this validation process. In macroeconomic time-series data the chronological order matters, so the folds were selected in a way that preserves this time order. I choose to report the median MAE because events like the Great Finanical Crisis might contaminate inference with outlying errors.

The goal of this cross-validation process is not to select components that show outstanding performance over a simple autoregressive model, but to filter out components that could be adding more noise than explaining the trade transmission channel. If any component reports a median MAE that falls below the one obtained from a simple autoregressive model, then the weather shocks included in that component have the ability to predict ToT movements that a historical growth rate could not predict, and therefore, should be included as an instrument.

Figure A1 shows the median MAE for each principal component in two countries; the United States and Germany. The horizontal red line shows the median MAE from the baseline autoregressive model. Points that fall below this line are selected as powerful principal components for that country. For example, in the United States, the median MAE was about 1.8 percentage points. While the first four components produced larger forecast errors, the fifth component produced smaller errors and therefore, is included in the set of valid PCs for the US.

The number of components tested in the cross-validation process is different for each country. For example, Germany has 26 components as shown in this figure, while in the case of Mexico, only the first six components with the largest eigenvalues explained at least 1% of total variance, so the remaining components were removed from the analysis to avoid introducing excess noise (see Figure B6 in the Appendix). Moreover, one component can be associated with many trading partners and weather variables, so a small number of selected components does not imply that only a small number of countries influence the domestic economy's ToT.

regressions in the sample period uses future values of ToT.

Components with very large eigenvalues might capture frequent weather events that do not influence external accounts, while components with smaller eigenvalues may capture least-frequent events that have pronounced effects on prices. The out-of-sample nature of the cross-validation methodology used here smooths any concern that smaller components might be capturing noise. Finally, components that produced larger median MAE than the threshold do not necessarily represent *bad* components. Instead, these components were simply not powerful enough to explain more than a historical growth rate could, and they are dropped out to avoid overfitting issues.

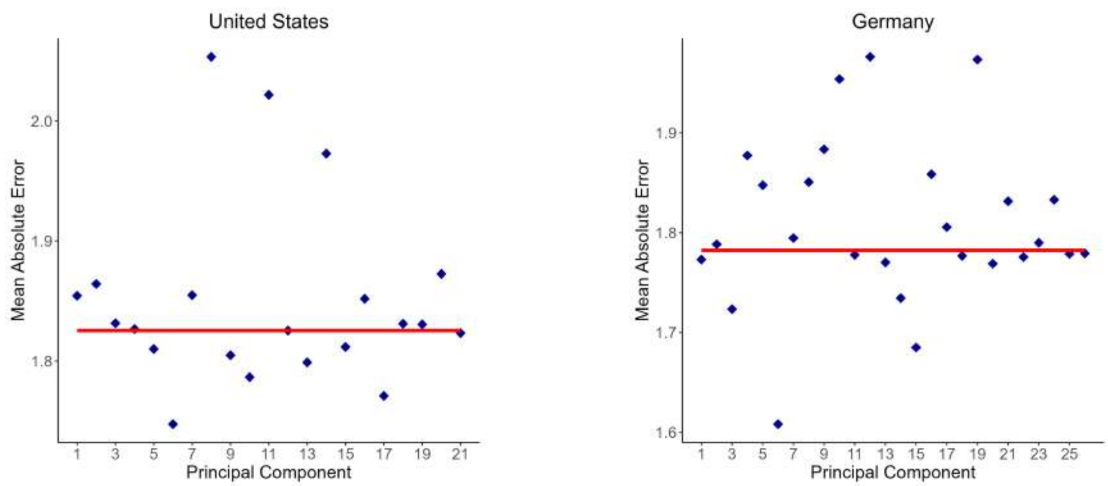

Figure A1: Principal Component Selection for Selected Countries

The two plots show how principal components were selected for two countries: the United States (on the LHS) and Germany (on the RHS). The principal components are arranged in descending order based on their eigenvalues. The **red**-colored straight line shows the median MAE of the baseline autoregressive model. Principal components with a smaller median MAE than the baseline model are characterized as powerful components and are included in the ToT instrument.

A.2 Weather Shocks

Table A1: Weather Variables Description

Variable	ID	Description	References
Baseline Model:			
Temperature Above 35°	TX35	Share of grid-days with maximum temperature above 35°	Akyapı et al. (2025)
Temperature Below 0°	TN0	Share of grid-days with minimum temperature below 0°	Akyapı et al. (2025)
Droughts	DROUGHT	Share of total grid-months subject to extreme and severe droughts (PDSI < -3)	Palmer (1965) and Akyapı et al. (2025)
High Moisture	MOISTURE	Share of total grid-months subject to high and extreme moisture (PDSI > 3)	Palmer (1965) and Akyapı et al. (2025)
Very Wet Day Precipitation	P95WT	Precipitation in very wet days (above the 95-th percentile)	Akyapı et al. (2025)
Heavy Precipitation Maximum	MAXP10	Max extent of heavy precipitation (greater than 10mm)	Akyapı et al. (2025)
Robustness Tests:			
Temperature Above 40°	TX40	Share of grid-days with maximum temperature above 40°	Akyapı et al. (2025)
Harsh Droughts	HDROUGHT	Share of total grid-months subject to extreme and severe droughts (PDSI < -4)	Palmer (1965) and Akyapı et al. (2025)
Very High Moisture	VHMOISTURE	Share of total grid-months subject to high and extreme moisture (PDSI > 4)	Palmer (1965) and Akyapı et al. (2025)
Extremely Wet Day Precipitation	P99WT	Precipitation in extremely wet days (above the 99-th percentile)	Akyapı et al. (2025)
Extreme Precipitation Maximum	MAXP20	Max extent of extreme precipitation (greater than 20mm)	Akyapı et al. (2025)

I estimate country-level weather shocks as the innovations of a VAR system of key climate variables. Let S_t^i be a vector of N_w weather variables observed in country i. The VAR model is:

$$S_t^i = \alpha_t + \sum_{p=1}^{P} \beta_{t,p} \; S_{t-p}^i + \upsilon_t^i \tag{A.3}$$

where υ_t^i are the reduced-form residuals. These residuals capture innovations that were not predicted by lagged values of the vector and can be perceived as weather anomalies, or otherwise, weather shocks. This methodology is a generalization of a standardized OLS approach followed by Hamilton (2018) and Bilal and Känzig (2024)–who extract temperature shocks as persistent temperature deviations from the long-term trend–and allows for the inclusion of a rich set of weather variables.

In the baseline methodology, I select $N_w = 6$ weather variables to enter a VAR model of order 4. These variables are described in table A1. The selection of 4 lags is standard in quarterly data. The data were provided by Akyapı et al. (2025) in monthly frequency and I aggregated them to quarterly data using a simple average. All weather shocks are standardized by their standard deviation, so they can be comparable when used in principal component analysis.[32] That is, for every country, i, and each weather variable, c:

$$\tilde{S}_{c,t}^i = \frac{\upsilon_{c,t}^i}{sd(\upsilon_{c,t}^i)} \tag{A.4}$$

Figure A2 shows the time series of these weather shocks in the United States. Analogous white-noise weather shocks were generated for all countries in the sample, but are omitted here for brievity.

A.3 Bilateral Trade Shares

I download trade data from the UN Comtrade (Trade File). The UN Comtrade offers three systems of classifications: the Harmonized System (HS), the Standard International Trade Classification (SITC) and the Broad Economic Categories (BEC). The selection of the classification system matters only when the user needs to download disaggregated series (e.g., imports and exports on meat products). To construct bilateral trade shares, this selection is not important because aggregated exports or imports have the same values across the classification choice. However, the periods covered in each classification can differ in practice. For example, while the HS system offers more refined data than SITC, and BEC, the data starts in 1988 while SITC goes back to 1962. While this would suggest the use of SITC as

[32] The series is already demeaned as these are the reduced-form residuals.

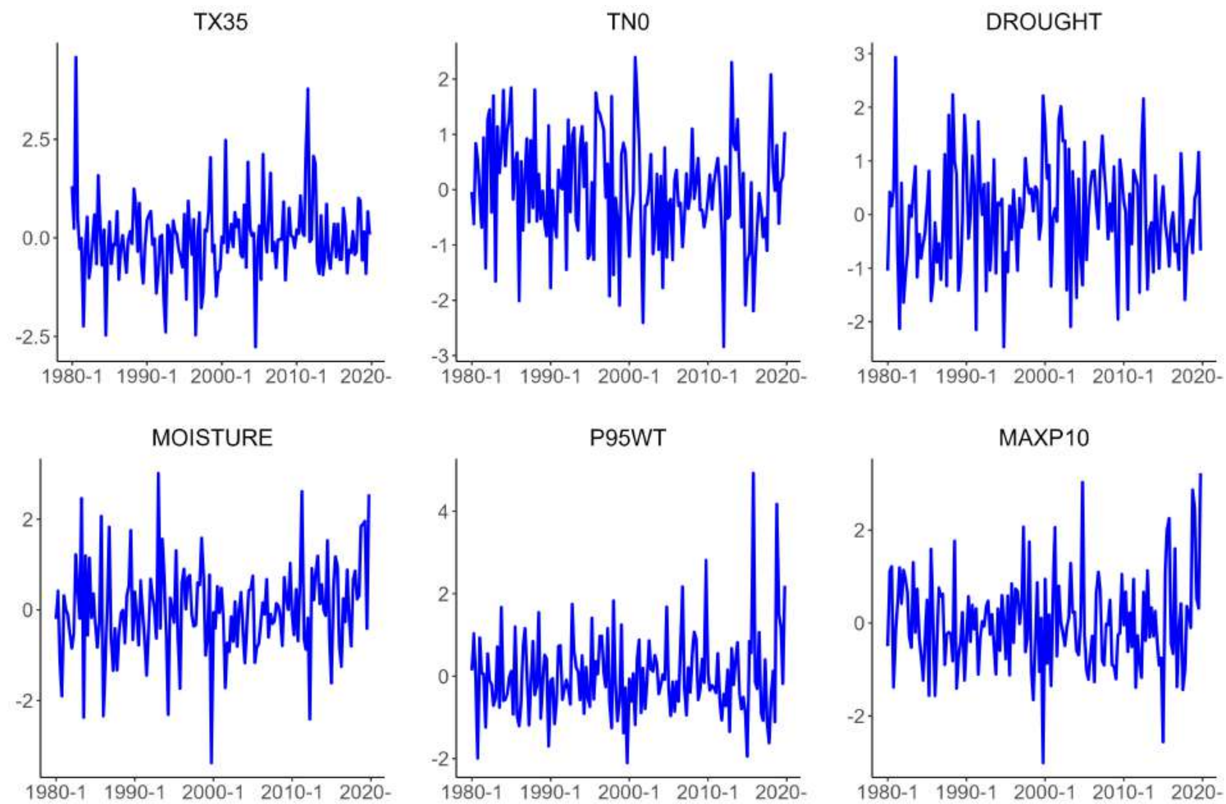

Figure A2: Weather Shocks in the United States

The figure shows six weather shocks in the US defined as the reduced-form residuals of a VAR model shown in Equation A.3. The shocks are standardized by their standard deviations.

long as the user is only interested in aggregated data, I noticed that this would result in some missing observations.

I download bilateral annual import and export values using the HS classification system from 1988 to 2024, and I supplement any missing observations with the SITC system. This approach allows me to exploit data on more countries and use the entire sample from 1962 to 2024. For example, SITC does not offer data for Iraq while the HS system offers from 2010 to 2016. Another example is Venezuela, where SITC has no data available, while HS has data from 1994 to 2013. Overall, there were 5 countries with data only available under HS. These were, the Cook islands, the Federated States of Micronesia, Iraq, Venezuela, and Vanuatu. From this list, only the Cook islands was not included in the climate data.[33]

[33]More specifically, I used the package ct_get_data in R. When the data are requested under HS, the function updates automatically for the most recent version. When I downloaded SITC data, I used the following versions to map the data: I downloaded years 1962-1999 with version S1, 2000-2009 with S3 and 2010-2024 with S4.

A.4 Macroeconomic Variables

I use quarterly macroeconomic data from the National Economic Accounts (NEA) provided by the International Monetary Fund (IMF). NEA dataset provides data on imports (M) and exports (X) of goods and servives, and gross domestic product (Y) (in current and constant values). I use these series to construct import and export prices, and the terms of trade (ToT):

$$P_{i,t}^{x} = \frac{X_{i,t}^{\$}}{X_{i,t}} \tag{A.5}$$

$$P_{i,t}^{m} = \frac{M_{i,t}^{\$}}{M_{i,t}} \tag{A.6}$$

$$x_{i,t} = ln(P_{i,t}^{x}/P_{i,t}^{m}) \times 100 \tag{A.7}$$

where the dollar sign (\$) in superscript indicates a nominal value. I also use data of final consumption expenditure (private sector) to get real consumption (C), and gross fixed capital formation to get real investment (I) and combine the external balance of goods and services (NX) with GDP (Y) data to estimate the net-export-to-GDP ratio:

$$NX_{i,t} = \frac{NX_{i,t}^{\$}}{Y_{i,t}^{\$}} \times 100 \tag{A.8}$$

I merge this data with the Consumer Price Index by the IMF to get the price index (P) and data on Labor Statistics by the IMF to get series of unemployment rate (U). I also get series of nominal exchange rate and real exchange rate from the Effective Exchange Rate dataset from IMF. The nominal effective exchange rate uses a weighted currency index. The real effective exchange rate is adjusted by relative consumer prices.

Finally, I use data on central bank policy rates from the Bank of International Settlements (BIS). The series is provided in monthly frequency and I convert it to quarterly using a simple average. I trim the upper 1% of these rates from the entire dataset to remove outliers.[34]

For each of the aforementioned series, I require a country to hold at least 20 years of data (which corresponds to 80 quarterly observations). I use ARIMA-X13 to adjust the macroeconomic variables for seasonality when this is needed.

[34] For countries like Estonia, Finland and Ireland (among others) who are members of Eurozone and the dataset did not provide the policy rates, I used the central bank rates from ECB for the period since they joined Eurozone.

A.5 Robustness Checks

Table A2 reports robustness tests for both the construction of the ToT shocks and their macroeconomic effects. The table reports the cumulative responses at horizons one year ($h = 4$), three years ($h = 12$) and five years forward ($h = 5$) for terms of trade (TOT), real exchange rate (RER), consumer price index (CPI), and real gross domestic product (real GDP). Unless noted otherwise, shocks are scaled so that the ToT declines by 10% at $h = 4$ quarters, and standard errors are clustered by country. Results are similar for double-clustered at country-time level, or wild-cluster bootstrap for small samples (not reported here).

Results are not driven by extremes.—I first assess whether estimates are influenced by outliers. Trimming the upper and lower 1% of ToT shocks within each country leaves impulse responses essentially unchanged. While some trimming of macro variables is part of the baseline procedure, further trimming of the upper and lower 1% of dependent variables for each country does not attenuate the IRFs; if anything, CPI and real GDP responses become somewhat larger.

I also test whether significance is driven by a small set of countries using a leave-one-country-out (LOCO) jackknife. Let θ^h denote the full-sample estimate (impact or cumulative) from the panel local projection at horizon h (see Equation 9), and let N be the number of countries. For each country i, let θ^h_{-i} be the estimate when country i is excluded. Then, the jackknife point estimate is:

$$\theta^h_J = N\theta^h - (N-1)\bar{\theta}^h \tag{A.9}$$

where, $\bar{\theta}^h$ is the average IRF from the LOCO process. I.e.:

$$\bar{\theta}^h = \frac{1}{N}\sum_i \theta^h_{-i} \tag{A.10}$$

and the jackknife standard errors are estimated by:

$$se(\theta^h_J) = \sqrt{\frac{N-1}{N}\sum_i \left(\theta^h_{-i} - \bar{\theta}^h\right)^2} \tag{A.11}$$

Across variables and horizons, LOCO impulse responses closely track the full-sample estimates, and jackknife standard errors are similar to baseline, indicating that no single country materially drives the results.

Impulse responses are robust to controls.—The baseline panel local projections model (Equation 9) includes country and time fixed effects, and four lags of the first difference of the dependent variable. The results are robust to several control variations summarized in Table A2. First, adding one lag of the ToT shock yields virtually identical responses. Second, replacing time fixed effects with global controls produces the same conclusions: when I include country-fixed effects and four lags of oil-price inflation, the estimated responses change little.

Robust Identification Strategy.—The principal components used to construct the synthetic ToT shock are selected via a simple cross-validation procedure: each component's out-of-sample predictive performance is evaluated relative to a baseline autoregressive model that includes four lags of the first difference of ToT. These autoregressive components do not enter the baseline synthetic regression (Equation 5) so as to preserve statistical power. As a check, I re-estimate the synthetic step including those lags; the resulting country-level shocks and downstream impulse responses are very similar.

I also test the importance of the selection step by omitting the *cross-validation* stage. I run two related tests. On the first one, I include *all* principal components in the synthetic regression (Equation 5). In the second, I follow a more standard approach and include the minimum number of components that cumulatively explain at least 80% of sample variance. The main conclusions are unchanged. Two minor differences emerge: CPI responses are somewhat larger on impact and at medium horizons, and real GDP responses arrive slightly earlier, although the cumulative five-year output response is modestly smaller than in the baseline.

Finally, I test the robustness of results when the principal components are not orthogonalized to domestic weather shocks. The results are quantitatively similar, but the response of CPI is stronger. This is probably due to the fact that when the domestic country's shocks are correlated with foreign weather shocks, the impulse responses are contaminated with domestic episodes that also influence ToT.

Robust Selection of Weather Shocks.—In the baseline, I use six weather variables to capture exogenous variation in ToT shocks (as shown in B1). I deliberately move beyond simple averages (e.g., changes of mean temperature or rainfall) because the climate literature shows that higher-moment and threshold events matter for output (see Akyapı et al. (2025)). A concern is that very rare "*extreme*" events (e.g., grid-days with maximum temperature exceeding 40^oC, or extreme droughts) occur infrequently and could add noise. As a robustness check, I augment the baseline weather vector S_t^i with additional measures that separate *severe* from *extreme* conditions. Concretely, I add the following set of variables:

$$S_t^{i\star} = \begin{bmatrix} TX35 - TX40 \\ DROUGHT - HRDROUGHT \\ MOISTURE - VHMOISTURE \\ P95WT - P99WT \\ MAXP10 - MAXP20 \end{bmatrix} \quad \text{(A.12)}$$

The augmented set of weather variables is $[S_t^i, S_t^{i\star}]'$.[35] I use this vector and re-run the same trade-weighting, PCA, and cross-validation pipeline used in the baseline.

The results (as seen in Table A2) are qualitatively similar and more pronounced: inflation rises more and real activity falls more following an adverse ToT shock when the weather menu includes these severe/extreme indicators. Standard errors are comparable to the baseline. This pattern is consistent with the idea that rare but intense weather disturbances carry higher signal for trade-related supply disruptions and thus strengthen the predictive content for ToT-driven macro responses, rather than merely adding noise.

The Trade Channel.—The baseline results indicate that transmission operates through trade: the identified shocks generate clear impulse responses in the terms of trade, the real exchange rate, real imports, and real exports. I run several robustness checks to evaluate the significance of the trade channel. As a first exercise, I re-estimate the identification strategy without pre-weighting foreign weather shocks by bilateral trade shares (BTS), so weather from weakly and strongly linked partners enters with equal weight. In this case, the real exchange rate still depreciates significantly, but medium-run cumulative effects on prices and activity become statistically insignificant. This loss of signal is consistent with dilution from low-exposure partners.

I then restrict the instrument to trading partners with strong exposure (i.e., $w_{y-1}^{i,j} > 10\%$ in Equation 3). The resulting IRFs are larger for CPI and real GDP than in the baseline, indicating that high-exposure partners drive the transmission. This suggests the baseline—which includes all partners—does not mechanically overstate effects.

Conversely, when I construct the instrument by keeping only small partners (i.e., $w_{y-1}^{i,j} < 1\%$ in Equation 3), the CPI response becomes insignificant and the real-GDP response remains marginally significant (at the 68% level) but smaller in magnitude. This pattern reinforces the view that trade exposure is the key margin.

[35] Note how the initial variables (e.g., $TX35$) now capture extreme events, while the added variables (e.g., $TX35-TX40$) are intended to capture severe but not extreme events. The result is an increase in the dimensions of weather events that can potentially capture nonlinearity, if say, unanticipated extreme weather shocks do not exhibit proportional increased effects compared to unanticipated severe weather shocks.

Finally, I replace the lagged-year BTS with a two-year moving average of lagged BTS in Equation 3. Responses are somewhat attenuated – especially for inflation – consistent with the idea that averaging dilutes current exposure when trade patterns adjust quickly.

The Financial Channel.—Are the spillover effects of identified ToT shocks really happening mainly through the trade channel? One concern is whether the domestic effects are heavily influenced by investors' response to foreign weather shocks. In Figure B4 I report the IRF of sovereign spread to the same adverse ToT shock as studied in the baseline results. The sovereign spread is defined as the spread between long-term yields versus the US long-term yields. Quarterly long-term yield data were obtained from OECD. The dataset covered data for 39 out of the 48 economies covered in this study, so the results should be interpreted with some caveat. The following countries were excluded: Albania, Bolivia, Costa Rica, Cyprus, Philippines, Paraguay, Singapore, Sweden and Turkey. It includes, however, countries who have reported large spreads–for example, Greece, Italy, Portugal, Mexico, Slovenia, Romania, India, Spain, and Brazil, among others. This alleviates concerns about selection bias.

The IRFs show that the sovereign spread does not respond to these shocks throughout the five-year horizon. The only exception is the sixth quarter where the response is only marginally significant at the 68% level. Evaluating the economic significance, the spread peaks at 50 basis points one and a half years after the shock occurs. Considering that the shock is severe enough to drop ToT by 10%, a lagged response of 50 bps does not seem to signal strong spillovers of the weather shocks through the *financial* channel. Notice how, on impact and during the first quarters, the response is essentially zero. This speaks to the identification of this strategy: Foreign weather shocks take some time to propagate. By the time they are observed, their effects have not yet materialized to the domestic economy. If investors perceived these shocks as a source of uncertainty they would raise their premiums on impact and that should reflect on these spreads. The negative ToT shock causes the quantity of imports to drop less than a year after the shock (as seen in the baseline results), and net exports fall because the relative prices respond more aggresively than the relative quantities traded. Combined, these results speak in favor of the *trade* channel versus the *financial* channel.

Similar Monetary Policy Response to Oil Supply News Shocks.—One way to understand the severity of the effects of ToT shocks is to compare them with a '*more familiar*' shock: an oil supply news shock. There are several reasons why. First, oil supply news shocks are considered exogenous and are informative of future supply shortages. Second, their effects are similar to the ToT effects in the sense that they are inflationary and contractionary. Third, without a doubt, monetary policymakers monitor these shocks and are ready to intervene if needed.

For what follows, let's simplify the monetary objective, such that the monetary authorities aim to protect prices (i.e., $\lambda = 0$ in the welfare loss function of Equation 13). Figure B5 compares the effects of an adverse ToT shock with an adverse oil supply news shock. The latter shocks are provided by Känzig (2021) and are estimated by a first-stage regression where country-level terms-of-trade growth is regressed on the news shock. That way, I transform a global shock into country-level series which enter the panel model 9, same as ToT shocks do.

In this exercise, both shocks are scaled to cause a cumulative inflation of 1 percent at the 5-year horizon. To make the welfare impact for both shocks interpretable, I scale all levels of welfare loss such as an oil supply news shock with no intervention causes a welfare loss of 100 at the five-year horizon. If the monetary authorities did not intervene, the weather-driven ToT shock would create a loss equivalent to 73% of what we would have seen under an equivalent oil supply news shock. Optimal intervention would then require a 35 bps increase in the policy rate on impact in the case of the weather-driven shock, and a 39 bps increase in the case of the oil supply news shock. In both cases, these optimal responses are expected to cause sizeable contractionary effects, reaching a trough after three years. However, as the welfare loss shows, intervention in both cases would offset most of the inflationary effects. In the case of the ToT shock, optimal intervention would drop the welfare loss to about 7.42% after 5 years, while in the case of the oil shock, the welfare loss under optimal intervention would drop to about 16.76%.

Table A2: Robustness Tests

	TOT			RER			CPI			Real GDP		
Horizon:	$h=4$	$h=12$	$h=20$	$h=4$	$h=12$	$h=20$	$h=4$	$h=12$	$h=20$	$h=4$	$h=12$	$h=20$
Baseline results	-10.000	-6.784	-7.721	-3.803	-3.619	-2.769	0.661	2.455	3.217	-0.386	-1.333	-1.450
	(1.360)	(1.388)	(1.034)	(0.963)	(1.238)	(1.143)	(0.846)	(2.212)	(2.775)	(0.493)	(0.776)	(0.916)
Trim ToT shocks	-10.000	-7.740	-7.567	-3.607	-3.587	-2.700	0.810	3.020	3.398	-0.477	-1.762	-1.456
	(1.462)	(1.592)	(1.157)	(1.082)	(1.544)	(1.307)	(1.021)	(2.630)	(3.117)	(0.563)	(0.886)	(0.962)
Trim macro variables	-10.000	-9.494	-8.151	-3.616	-4.161	-2.828	0.234	1.742	3.839	-0.751	-2.101	-3.046
	(1.514)	(1.894)	(1.147)	(1.087)	(1.583)	(1.407)	(0.603)	(1.614)	(2.835)	(0.547)	(1.060)	(1.269)
Add autoregressive controls in synthetic regression (Eq 5)	-10.000	-6.788	-7.595	-3.743	-3.203	-2.460	1.118	2.973	4.474	-0.434	-1.579	-1.526
	(1.402)	(1.469)	(1.099)	(0.974)	(1.172)	(1.027)	(1.129)	(3.738)	(5.328)	(0.494)	(0.754)	(0.879)
Control for lagged ToT shock in panel LP (Eq 9)	-10.000	-6.711	-7.727	-3.885	-3.656	-2.782	0.804	2.447	3.123	-0.366	-1.274	-1.388
	(1.325)	(1.332)	(1.005)	(0.971)	(1.268)	(1.170)	(0.844)	(2.145)	(2.612)	(0.496)	(0.780)	(0.921)
Control for Oil Price Inflation in panel LP (Eq 9)	-10.000	-7.047	-7.959	-3.636	-3.829	-3.559	2.236	4.532	5.621	-0.176	-2.078	-1.658
	(1.189)	(1.318)	(1.221)	(1.008)	(1.292)	(1.152)	(1.398)	(3.104)	(4.330)	(0.598)	(0.786)	(0.889)
Leave-one-country-out Panel LP	-10.000	-6.820	-7.713	-3.718	-3.524	-2.747	0.706	2.728	3.641	-0.351	-1.312	-1.418
	(0.000)	(1.081)	(0.831)	(1.075)	(1.376)	(1.136)	(0.967)	(2.516)	(3.118)	(0.510)	(0.767)	(0.917)
Extreme weather shocks	-10.000	-7.596	-8.274	-4.425	-5.565	-3.476	2.281	5.481	4.497	-0.006	-1.406	-1.958
	(1.422)	(1.874)	(1.393)	(1.002)	(1.203)	(1.149)	(1.614)	(3.298)	(2.730)	(0.305)	(0.761)	(0.971)
Include all principal components in synthetic regression (Eq 5)	-10.000	-6.016	-7.208	-2.926	-3.408	-2.987	2.407	4.017	5.116	-0.793	-1.435	-1.034
	(1.389)	(1.178)	(0.988)	(0.910)	(1.043)	(1.028)	(1.289)	(2.873)	(3.647)	(0.343)	(0.621)	(0.774)
Keep min principal components that explain at least 80% of variance	-10.000	-5.949	-7.651	-2.710	-3.435	-2.744	2.338	3.992	4.842	-0.824	-1.223	-0.944
	(1.417)	(1.385)	(1.100)	(0.932)	(1.091)	(1.064)	(1.497)	(3.037)	(3.709)	(0.374)	(0.650)	(0.819)
Historical 2-Year BTS average	-10.000	-6.789	-7.053	-3.663	-4.078	-3.026	0.750	1.548	1.235	-0.610	-0.930	-1.070
	(1.455)	(1.449)	(1.151)	(0.947)	(1.179)	(1.089)	(0.764)	(1.478)	(2.023)	(0.456)	(0.806)	(1.010)
No BTS pre-weighting	-10.000	-6.337	-6.841	-3.533	-3.602	-2.504	0.376	0.126	-0.472	0.609	-0.258	-0.461
	(1.580)	(1.317)	(1.208)	(0.961)	(0.891)	(1.166)	(0.604)	(1.146)	(1.947)	(0.351)	(0.671)	(0.850)
Big trading partners (BTS > 10 %)	-10.000	-7.263	-8.288	-3.975	-2.954	-2.348	0.736	3.112	5.196	-0.542	-1.783	-1.823
	(1.346)	(1.758)	(1.827)	(1.239)	(1.816)	(1.814)	(0.794)	(3.421)	(4.968)	(0.731)	(1.116)	(1.543)
Small trading partners (BTS < 1 %)	-10.000	-5.683	-5.640	-3.042	-2.009	-0.083	-0.603	-0.816	-1.198	0.293	-0.606	-0.791
	(1.441)	(1.197)	(0.833)	(1.004)	(0.896)	(0.751)	(0.707)	(1.086)	(1.985)	(0.265)	(0.567)	(0.614)
Non-orthogonalized components	-10.000	-6.647	-7.685	-3.787	-3.685	-2.665	1.900	5.286	7.526	-0.634	-1.294	-1.339
	(1.452)	(1.256)	(1.088)	(0.955)	(1.293)	(1.317)	(1.109)	(3.575)	(5.320)	(0.442)	(0.768)	(0.924)

A.6 Data Citation

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Appendix B Additional Tables & Figures

Table B1: Descriptive Statistics of ToT Shocks

ISO	Country	First Obs.	Last Obs.	Minimum	$Q1$	Median	$Q3$	Maximum	Correlation (%)	CI (Low)	CI (High)
ALB	Albania	1997 Q1	2019 Q4	-0.43	-0.12	0.02	0.12	0.32	17.08	-0.18	33.36
AUS	Australia	1980 Q1	2019 Q4	-1.01	-0.18	0.02	0.18	0.61	30.29	17.95	41.69
AUT	Austria	1980 Q1	2019 Q4	-0.43	-0.10	0.00	0.13	0.44	23.01	6.63	38.18
BEL	Belgium	1980 Q1	2019 Q4	-0.43	-0.11	0.01	0.10	0.42	19.72	3.19	35.19
BGR	Bulgaria	1997 Q1	2019 Q4	-0.34	-0.10	-0.01	0.10	0.45	14.92	-2.40	31.37
BOL	Bolivia	1980 Q1	2019 Q4	-1.03	-0.26	-0.02	0.23	1.08	36.02	22.07	48.52
BRA	Brazil	1980 Q1	2019 Q4	-0.83	-0.12	-0.00	0.11	1.03	26.51	9.97	41.62
CAN	Canada	1980 Q1	2019 Q4	-0.46	-0.08	-0.01	0.08	0.35	13.88	0.85	26.46
CHE	Switzerland	1980 Q1	2019 Q4	-0.82	-0.19	-0.01	0.16	0.96	26.33	10.15	41.16
CHL	Chile	1980 Q1	2019 Q4	-1.23	-0.26	-0.00	0.23	1.03	35.82	20.05	49.77
CRI	Costa Rica	1980 Q1	2019 Q4	-0.41	-0.09	-0.01	0.11	0.40	18.84	3.52	33.29
CYP	Cyprus	1980 Q1	2019 Q4	-1.13	-0.14	-0.00	0.15	0.63	24.70	8.06	40.01
CZE	Czech Republic	1994 Q1	2019 Q4	-0.49	-0.11	0.02	0.10	0.45	17.61	1.01	33.27
DEU	Germany	1980 Q1	2019 Q4	-0.83	-0.21	0.01	0.23	0.97	36.81	22.68	49.42
DNK	Denmark	1980 Q1	2019 Q4	-0.24	-0.06	0.00	0.05	0.27	16.12	0.72	30.77
ESP	Spain	1980 Q1	2019 Q4	-1.01	-0.27	-0.05	0.24	1.05	40.10	25.15	53.19
EST	Estonia	1996 Q1	2019 Q4	-0.60	-0.19	0.00	0.13	0.83	29.63	13.40	44.30
FIN	Finland	1980 Q1	2019 Q4	-1.28	-0.22	-0.01	0.27	0.88	38.70	25.01	50.87
FRA	France	1980 Q1	2019 Q4	-0.93	-0.24	-0.01	0.25	0.90	34.06	21.94	45.14
GBR	United Kingdom	1980 Q1	2019 Q4	-0.15	-0.03	0.00	0.03	0.13	8.54	-4.56	21.36
GRC	Greece	1980 Q1	2019 Q4	-0.73	-0.18	-0.00	0.19	0.92	32.06	16.30	46.23
HRV	Croatia	1993 Q1	2019 Q4	-0.32	-0.07	0.01	0.06	0.33	13.94	-2.76	29.88
HUN	Hungary	1980 Q1	2019 Q4	-0.37	-0.06	-0.01	0.05	0.56	15.97	-0.68	31.76
IND	India	1980 Q1	2019 Q4	-1.52	-0.36	-0.00	0.33	1.72	49.18	35.05	61.12
IRL	Ireland	1980 Q1	2019 Q4	-1.32	-0.16	0.01	0.20	0.97	28.90	12.88	43.44
ISL	Iceland	1980 Q1	2019 Q4	-0.90	-0.22	-0.02	0.23	0.82	35.33	19.87	49.08
ISR	Israel	1980 Q1	2019 Q4	-0.80	-0.21	0.02	0.17	0.98	31.01	15.16	45.31
ITA	Italy	1980 Q1	2019 Q4	-0.81	-0.15	0.02	0.15	0.86	32.64	16.58	47.02
JPN	Japan	1980 Q1	2019 Q4	-0.39	-0.10	-0.00	0.09	0.74	18.77	2.55	34.03
KOR	Korea, Rep.	1980 Q1	2019 Q4	-0.69	-0.11	0.01	0.11	0.37	21.11	8.28	33.24
LTU	Lithuania	1995 Q1	2019 Q4	-0.51	-0.14	-0.03	0.08	1.27	27.40	11.29	42.12
LUX	Luxembourg	2000 Q1	2019 Q4	-0.52	-0.18	-0.01	0.15	0.55	28.97	11.03	45.07
LVA	Latvia	1995 Q1	2019 Q4	-0.70	-0.14	0.01	0.15	0.62	23.82	7.48	38.91
MEX	Mexico	1980 Q1	2019 Q4	-0.43	-0.08	-0.00	0.07	0.38	15.65	-0.35	30.87
NLD	Netherlands	1980 Q1	2019 Q4	-0.76	-0.13	0.01	0.15	0.77	27.08	10.95	41.83
NOR	Norway	1980 Q1	2019 Q4	-1.27	-0.06	-0.00	0.08	0.41	23.27	10.01	35.72
NZL	New Zealand	1980 Q1	2019 Q4	-1.03	-0.23	0.00	0.19	1.06	33.89	20.39	46.11
PHL	Philippines	1980 Q1	2019 Q4	-0.89	-0.21	-0.05	0.22	1.32	31.53	19.07	43.00
POL	Poland	1981 Q1	2019 Q4	-0.75	-0.13	0.01	0.17	0.55	26.63	10.46	41.43
PRT	Portugal	1980 Q1	2019 Q4	-0.43	-0.10	-0.00	0.09	0.51	21.89	5.45	37.16
PRY	Paraguay	1980 Q1	2019 Q4	-0.01	-0.00	-0.00	0.00	0.01	0.24	-16.06	16.54
ROU	Romania	1990 Q1	2019 Q4	-0.51	-0.15	-0.02	0.10	1.92	28.69	12.66	43.25
SGP	Singapore	1980 Q1	2019 Q4	-1.39	-0.18	0.01	0.18	0.90	36.42	24.54	47.23
SVK	Slovak Republic	1995 Q1	2019 Q4	-0.72	-0.19	-0.01	0.20	0.73	30.03	14.10	44.44
SVN	Slovenia	1993 Q1	2019 Q4	-1.14	-0.20	0.02	0.23	0.69	36.24	20.87	49.87
SWE	Sweden	1980 Q1	2019 Q4	-0.45	-0.12	-0.02	0.12	0.71	19.60	3.72	34.51
TUR	Turkey	1980 Q1	2019 Q4	-0.96	-0.27	-0.03	0.23	1.70	42.02	26.22	55.62
USA	United States	1980 Q1	2019 Q4	-0.48	-0.09	0.00	0.08	0.45	22.76	10.00	34.78
EA	Euro Area	1996 Q1	2019 Q4	-0.49	-0.18	0.01	0.13	0.62	49.09	35.03	60.99

The table shows descriptive statistics of terms-of-trade shocks identified with foreign weather shocks. Columns 5-9 show the minimum value, the three quartiles, and the maximum value of the standardized shocks and are interpreted as the number of standard deviations away from mean (see Equation 6). Column 10 reports the Pearson Correlation of the non-standardized ToT shocks with the realized ToT cumulative growth rate from $t-1$ to $t+4$. Columns 11 and 12 show the corresponding confidence intervals at the 90% level. ToT shocks were estimated for the Euro-Area by aggregating the EA-19 member countries with consumption weights provided by Eurostat. The EA shocks do not enter the local projections as its member countries are already included separately.

Table B2: Descriptive Statistics of Year-on-Year Terms of Trade Growth Rates

ISO	Min	$Q1$	Median	Mean	$Q3$	Max	Stand. Dev.
ALB	-13.62	-2.54	0.09	-0.44	2.33	14.44	4.79
AUS	-19.64	-3.81	0.86	1.36	5.71	22.57	7.98
AUT	-7.27	-1.37	-0.44	-0.35	0.69	5.80	1.81
BEL	-5.68	-1.13	-0.14	-0.29	0.46	4.06	1.50
BGR	-25.62	-0.80	1.69	1.83	3.77	47.63	7.56
BOL	-27.30	-6.11	-0.05	-0.24	6.31	29.84	9.96
BRA	-13.25	-3.63	-0.57	0.05	3.74	14.18	6.05
CAN	-16.09	-2.39	0.16	0.28	3.25	18.47	4.58
CHE	-4.05	-1.36	-0.34	-0.30	0.72	3.27	1.56
CHL	-30.92	-3.21	1.08	2.44	7.68	31.34	10.14
CRI	-11.45	-2.56	0.26	0.14	2.84	11.54	4.06
CYP	-7.66	-0.72	0.19	0.08	1.11	7.91	1.75
CZE	-4.94	-0.89	0.50	0.47	1.67	10.64	2.56
DEU	-4.62	-1.47	0.53	0.23	1.70	5.69	2.21
DNK	-10.34	-0.54	0.58	0.23	1.41	5.27	2.17
ESP	-9.04	-1.51	0.32	0.20	1.96	8.75	2.88
EST	-5.28	-0.39	0.81	1.15	2.81	7.87	2.40
FIN	-6.89	-2.29	-0.62	-0.58	0.72	11.00	2.63
FRA	-6.69	-1.28	-0.10	0.05	1.11	9.70	2.26
GBR	-7.57	-1.09	0.73	0.40	1.85	6.22	2.28
GRC	-9.12	-1.39	0.21	0.52	2.38	9.92	3.34
HRV	-6.62	-0.12	0.70	0.65	1.87	7.24	2.15
HUN	-7.16	-1.20	-0.09	-0.09	1.00	9.57	2.22
IND	-42.08	-2.89	-0.27	0.13	4.64	26.87	8.22
IRL	-6.77	-2.20	-0.72	-0.53	1.03	8.34	2.72
ISL	-12.46	-2.90	-0.86	-0.49	2.11	11.56	4.48
ISR	-11.67	-1.97	0.23	0.39	2.69	9.78	3.55
ITA	-12.61	-2.05	0.17	-0.06	2.32	12.44	3.87
JPN	-15.21	-5.39	-2.07	-1.70	1.66	15.74	5.86
KOR	-14.01	-4.31	-0.68	-0.96	2.43	10.13	4.92
LTU	-11.03	-1.59	0.88	0.86	3.11	15.78	4.56
LUX	-4.55	-0.81	0.10	0.34	1.33	11.39	2.14
LVA	-14.06	-1.46	0.66	0.28	2.56	10.63	3.83
MEX	-16.71	-3.08	0.45	0.54	4.33	17.82	5.83
NLD	-4.44	-0.57	0.14	0.13	0.99	4.35	1.50
NOR	-53.72	-6.02	0.27	0.89	5.67	64.78	15.16
NZL	-12.77	-2.65	0.40	0.71	4.05	17.17	5.06
PHL	-19.37	-4.08	-0.53	-0.00	2.54	28.33	7.38
POL	-11.25	-1.92	0.19	-0.05	2.43	8.57	3.64
PRT	-5.38	-1.23	0.44	0.46	2.14	6.92	2.36
PRY	-15.39	-4.72	0.13	-0.22	3.42	20.54	6.71
ROU	-9.52	-0.26	1.79	2.20	4.78	15.26	4.29
SGP	-4.63	-0.83	0.25	0.27	1.13	4.62	1.62
SVK	-10.17	-1.73	-0.52	-0.75	-0.04	8.49	2.34
SVN	-5.07	-1.32	0.27	0.04	1.26	5.48	2.08
SWE	-3.84	-1.24	-0.23	-0.28	0.62	3.66	1.34
TUR	-20.46	-4.61	-0.03	-0.61	3.20	24.77	7.30
USA	-16.86	-1.24	0.54	0.15	1.84	8.14	3.24
EA	-5.94	-1.47	0.08	-0.04	1.30	4.65	2.10
Median:[(1)]	**-10.68**	**-1.55**	**0.19**	**0.14**	**2.23**	**10.38**	**3.44**

The table shows descriptive statistics of year-over-year (%) growth rates of terms of trade in a panel of 48 economies with quarterly data from 1980-2024. Column 2 reports the minimum growth rate. Columns 3-6 report the 3 quartiles and the mean. Column 7 shows the maximum growth rate. Column 8 reports the standard deviation. The last row reports the cross-country median for these statistics. Footnotes: (1) The aggregated observation for the Euro Area is excluded to avoid duplication.

Table B3: Descriptive Statistics of Sample Countries

ISO	Fixed	Float	Price Setter	Price Taker	Income	Trade Openness	Debt	Agriculture	Gov Effectiveness
ALB	88	0		Yes	Below	Below	Above	Above	Below
AUS	11	149	Yes		Above	Below	Above	Above	Above
AUT	160	0		Yes	Above	Above	Above	Below	Above
BEL	160	0		Yes	Above	Above	Above	Below	Below
BOL	129	3		Yes	Below	Below	Below	Above	Below
BRA	21	82	Yes		Below	Below	Above	Above	Below
CAN	89	71	Yes		Above	Below	Below	Below	Above
CHE	14	146		Yes	Above	Above	Below	Below	Above
CHL	10	148	Yes		Below	Below	Below	Above	Below
CRI	119	30		Yes	Below	Below	Below	Above	Below
CYP	160	0		Yes	Below	Above	Above	Below	Below
CZE	43	61		Yes	Below	Above	Below	Below	Below
DEU	84	76	Yes		Above	Below	Below	Below	Above
DNK	160	0		Yes	Above	Above	Below	Below	Above
ESP	160	0		Yes	Below	Below	Above	Above	Below
EST	96	0		Yes	Below	Above	Below	Above	Above
FIN	157	0		Yes	Above	Above	Above	Above	Above
FRA	160	0	Yes		Above	Below	Above	Below	Above
GBR	0	160	Yes		Above	Below	Above	Below	Above
GRC	148	12		Yes	Below	Above	Above	Above	Below
HRV	101	0		Yes	Below	Above	Above	Above	Below
HUN	0	0		Yes	Below	Above	Above	Above	Below
IND	116	44	Yes		Below	Below	Above	Above	Below
IRL	160	0		Yes	Above	Above	Above	Below	Above
ISL	56	90		Yes	Above	Above	Above	Above	Above
ISR	15	120		Yes	Above	Below	Below	Below	Above
ITA	145	12	Yes		Above	Below	Above	Below	Below
JPN	0	160	Yes		Above	Below	Above	Below	Above
KOR	71	86	Yes		Above	Below	Below	Below	Above
LTU	100	0		Yes	Below	Above	Below	Above	Below
LUX	160	0		Yes	Above	Above	Below	Below	Above
LVA	56	44		Yes	Below	Above	Below	Above	Below
MEX	28	99	Yes		Below	Below	Below	Above	Below
NLD	160	0		Yes	Above	Above	Below	Below	Above
NOR	0	160	Yes		Above	Below	Below	Below	Above
NZL	0	160	Yes		Above	Below	Below	Above	Above
PHL	122	31		Yes	Below	Below	Below	Above	Below
PRT	156	4		Yes	Below	Above	Above	Above	Above
PRY	34	114		Yes	Below	Below	Below	Above	Below
ROU	67	8		Yes	Below	Above	Below	Above	Below
SGP	15	145		Yes	Above	Above	Above	Below	Above
SVK	100	0		Yes	Below	Above	Above	Below	Below
SVN	0	0		Yes	Below	Above	Above	Below	Below
SWE	89	71		Yes	Above	Above	Below	Below	Above
TUR	0	85	Yes		Below	Below	Below	Above	Below
USA	0	160	Yes		Above	Below	Above	Below	Above

The table shows descriptive statistics of the sample countries. Columns 2 and 3 show the number of (within-sample) periods for which a country adopted a *fixed* or a *floating* exchange rate system. I use the dataset by Ilzetzki et al. (2022) to determine these two regimes. Specifically, I used their coarse data and converted their monthly series to quarterly using end-of-quarter values. I grouped the hard and soft peg categories together as a *fixed* exchange regime and the intermediate and float as a *floating* exchange rate regime. Columns 4 and 5 report whether the country is grouped as a price setter or a price taker on global trade. A country is characterized as 'price setter' if its a G20 member country or a large commodity producer, and as 'price taker' otherwise. Columns 6-10 report whether the country is located above or below the median considering the following statistics: GDP per Capita (column 6), Trade-to-GDP ratio (column 7), Debt-to-GDP ratio (Column 8) and Government Efficiency index (column 9). Statistics for Columns 6-8 were provided by the World Development Indicators data (WDI) by the World Bank (as of 2019). Data on government effectiveness were provided by the Worldwide Governance Indicators (WGI) data by the World Bank.

Table B4: Local Projections Results

	Impact Effect	5 Year Effect	Effect at Peak/Trough			Observations	
Response	Estimate	Estimate	Horizon	Estimate	Within R^2 (%)	Max	Min
Terms of Trade	-2.140 (0.525)	-7.721 (1.034)	4	-10.000 (1.360)	7.35	5206	5202
Nominal Exchange Rate	-0.338 (0.699)	-5.521 (6.498)	15	-11.367 (3.245)	12.35	5948	5929
Real Exchange Rate	-0.879 (0.318)	-2.769 (1.143)	7	-4.483 (1.171)	1.57	5768	5764
Net Exports (% of GDP)	-0.451 (0.343)	0.263 (0.697)	4	-1.334 (0.671)	8.96	4944	4921
Real Exports	0.244 (0.533)	3.899 (2.159)	19	4.012 (2.132)	0.55	5206	5202
Real Imports	-0.450 (0.558)	-4.083 (2.129)	9	-7.315 (1.789)	1.14	5206	5202
Consumer Price Index	0.152 (0.139)	3.217 (2.775)	18	3.383 (2.763)	43.69	6082	6042
Real GDP	-0.054 (0.159)	-1.450 (0.916)	11	-1.589 (0.771)	3.05	5206	5202
Unemployment	0.072 (0.058)	0.341 (0.441)	9	0.520 (0.297)	5.77	4908	4873
Real Consumption	-0.406 (0.152)	-3.239 (1.050)	17	-3.890 (0.969)	0.66	5033	5029
Real Investment	-1.600 (0.685)	-8.192 (2.794)	9	-9.728 (2.461)	1.94	5126	5122
Policy Rate	0.172 (0.132)	-0.292 (0.287)	3	0.297 (0.163)	2.25	4483	4441

The table shows the impulse responses of key macroeconomic variables to a negative ToT shock that causes a 10% fall of ToT 1 year forward. The IRFs are estimated with the local projections model 9 in a panel of 48 countries over the period 1980-2019. All macro variables in the panel are expressed in $log \times 100$ format except for unemployment and the policy rates which enter as %. Country-clustered standard errors are reported in parentheses. Column 2 shows the impact effect ($h = 0$). Column 3 shows the cumulative effect at a 5-year horizon ($h = 20$). Columns 4-6 report estimates at peak or trough with column 4 showing the horizon at which the peak/trough occurs. Columns 7-8 show the maximum and minimum number of observations in regressions. The number of observations vary depending on the horizon and macro variable (due to data availability).

Table B5: Akaiki Information Criterion to Determine Number of Lags on Autoregressive Model of Global Commodity Prices

ISO	Optimal Lags	AIC	ISO	Optimal Lags	AIC
ALB	2	911.09	IRL	2	930.79
AUS	1	873.35	ISL	2	1053.20
AUT	2	916.59	ISR	2	1172.60
BEL	1	343.97	ITA	2	954.09
BGR	0	758.97	JPN	2	1104.04
BOL	1	995.04	KOR	2	1012.13
BRA	0	887.70	LTU	5	490.42
CAN	1	795.04	LUX	2	565.32
CHE	2	1017.92	LVA	2	625.61
CHL	3	1050.68	MEX	5	1094.01
CRI	2	1115.49	NLD	0	602.73
CYP	2	1171.45	NOR	5	1153.14
CZE	2	591.26	NZL	3	842.31
DEU	2	938.16	PHL	2	1068.89
DNK	2	853.44	POL	2	888.28
ESP	2	975.84	PRT	2	973.82
EST	4	515.03	PRY	2	1006.60
FIN	3	866.13	ROU	5	853.84
FRA	2	959.99	SGP	2	685.65
GBR	5	663.50	SVK	1	546.85
GRC	2	957.33	SVN	2	656.72
HRV	2	610.85	SWE	2	843.00
HUN	5	838.47	TUR	2	1062.92
IND	5	1033.00	USA	5	1060.23

The table shows the optimal number of lags using the Akaiki information criterion (AIC) on country-specific regressions of model 11. This model is used to identify innovations of global commodity prices with country-level Commodity Net Export Price Index data from Gruss and Kebhaj (2019).

Table B6: Estimated Optimal Monetary Policy Response Coefficients

Welfare Horizon:	Baseline ($\mathcal{H} = 20$)			Short ($\mathcal{H} = 10$)			Long ($\mathcal{H} = 40$)		
λ	$\hat{\psi}$	se($\hat{\psi}$)	R^2	$\hat{\psi}$	se($\hat{\psi}$)	R^2	$\hat{\psi}$	se($\hat{\psi}$)	R^2
0.00	45.64	2.76	89.92	48.32	10.70	63.11	22.03	7.15	32.66
0.05	39.71	3.14	72.93	31.89	10.81	36.10	20.08	6.68	27.57
0.10	34.25	4.28	58.08	21.46	10.88	20.42	18.13	6.35	22.86
0.15	29.21	5.20	45.20	14.25	10.52	10.88	16.19	6.14	18.55
0.20	24.55	5.82	34.13	8.98	9.80	5.09	14.26	5.93	14.63
0.25	20.23	6.28	24.75	4.95	9.13	1.79	12.33	5.80	11.14
0.30	16.20	6.51	16.96	1.77	8.48	0.26	10.41	5.54	8.09
0.35	12.45	6.55	10.69	-0.80	7.83	0.06	8.50	5.40	5.50
0.40	8.94	6.43	5.88	-2.92	7.14	0.91	6.60	5.25	3.37
0.45	5.65	6.31	2.51	-4.71	6.88	2.61	4.71	5.16	1.75
0.50	2.56	6.02	0.55	-6.22	6.24	5.06	2.82	5.01	0.64
0.55	-0.35	5.77	0.01	-7.53	5.78	8.15	0.94	4.89	0.07
0.60	-3.09	5.33	0.91	-8.67	5.57	11.85	-0.93	4.61	0.07
0.65	-5.67	4.83	3.30	-9.67	5.23	16.11	-2.79	4.48	0.66
0.70	-8.12	4.45	7.22	-10.56	4.82	20.91	-4.64	4.32	1.88
0.75	-10.44	4.00	12.78	-11.35	4.55	26.25	-6.49	4.09	3.74
0.80	-12.64	3.49	20.07	-12.06	4.33	32.12	-8.34	3.91	6.30
0.85	-14.72	3.12	29.26	-12.70	4.25	38.56	-10.17	3.74	9.57
0.90	-16.71	2.73	40.51	-13.28	3.99	45.56	-11.99	3.57	13.61
0.95	-18.60	2.62	54.07	-13.81	4.02	53.16	-13.81	3.49	18.45
1.00	-20.40	2.63	70.22	-14.29	3.92	61.41	-15.63	3.41	24.14

The table shows the estimated optimal monetary policy response coefficients over 3 different welfare horizons ($\mathcal{H}$) and 21 different welfare weights (λ). The optimal response coefficients are estimated with an OLS regression (see Equation 18). Bootstrapped standard errors from 10,000 runs are reported in this table. I choose a welfare horizon of 5 years to report the baseline results ($\mathcal{H} = 20$). Results for a shorter horizon of 2.5 years ($\mathcal{H} = 10$) and a longer horizon of 7.5 years ($\mathcal{H} = 30$) are also reported.

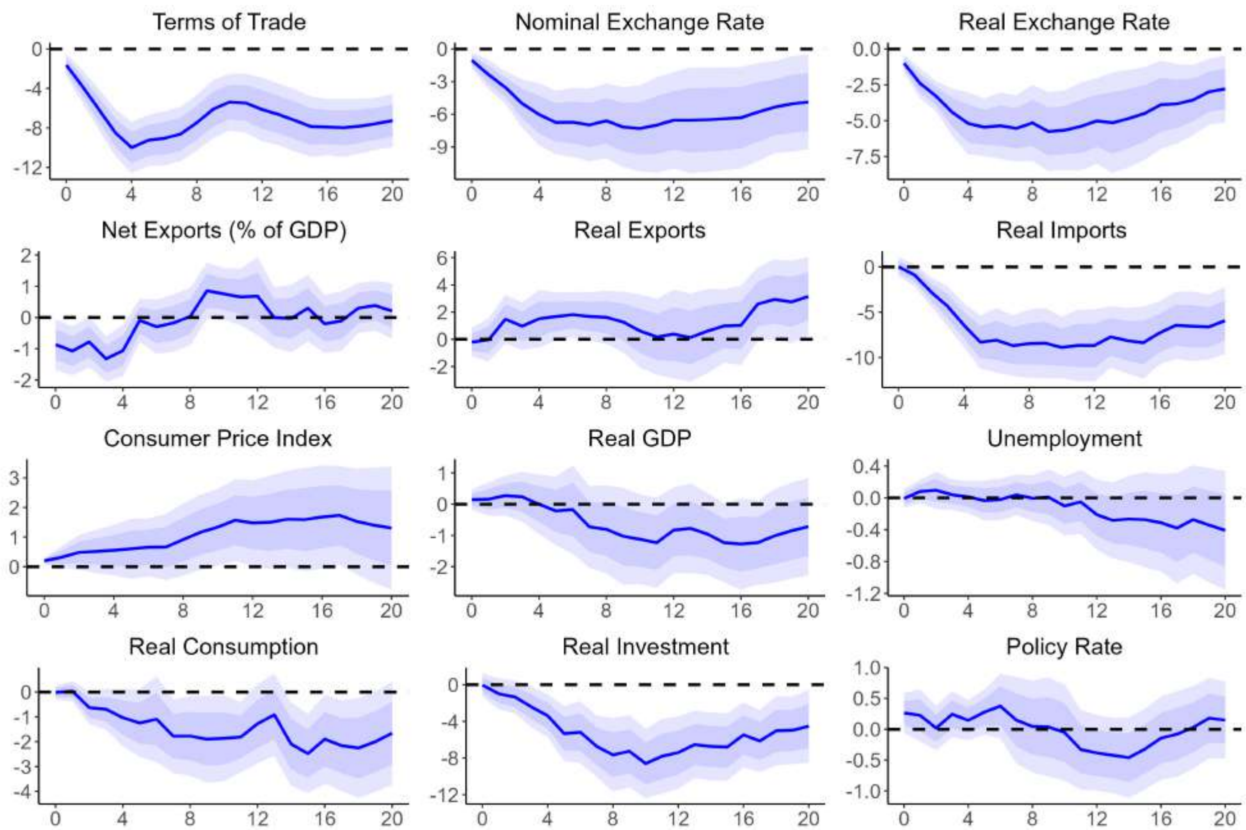

Figure B1: IRF of Floating Exchange Rate Regimes to a Negative ToT Shock

The figure plots the IRF of key macroeconomic variables to a negative ToT shock that causes a 10% fall of ToT 1 year forward. The IRFs are estimated for countries that preserved a floating exchange rate system at the time of the shock. The IRFs are estimated using panel local projections (model 10) over the period 1980-2019. All macro variables in the panel are expressed in $log \times 100$ format except for unemployment and the policy rates which enter as %. The confidence intervals are estimated with country-clustered standard errors at the 68% level.

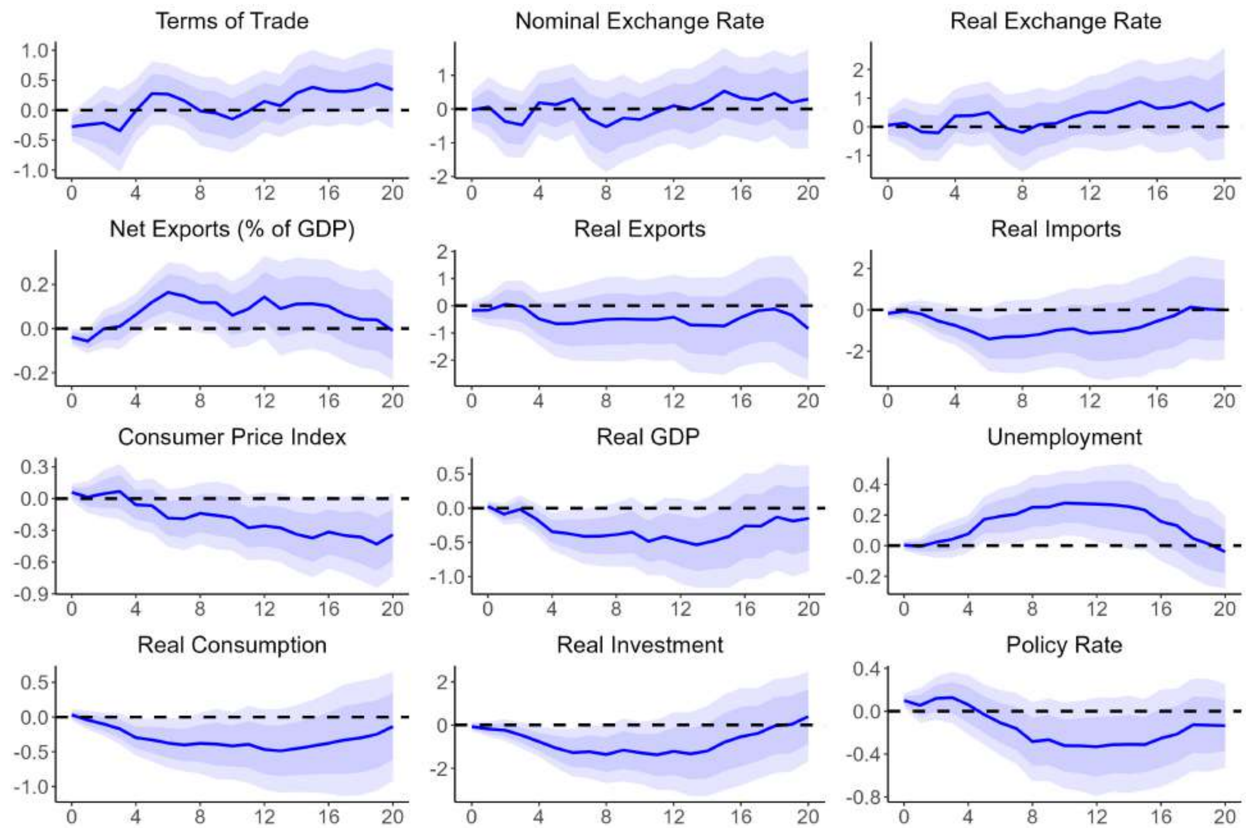

Figure B2: IRF to a Contractionary Monetary Policy Shock

The figure plots the IRF of key macroeconomic variables to a positive monetary policy shock that causes the policy rate to increase by 10 basis points on impact. The IRFs are estimated for the United States using monetary policy instruments from Bauer and Swanson (2023) over the period 1989-2019. The instrument is orthogonalized to macroeconomic announcements. All macro variables in the panel are expressed in $log \times 100$ format except for unemployment and the policy rates which enter as %. The confidence intervals are estimated with country-clustered standard errors at the 68% level.

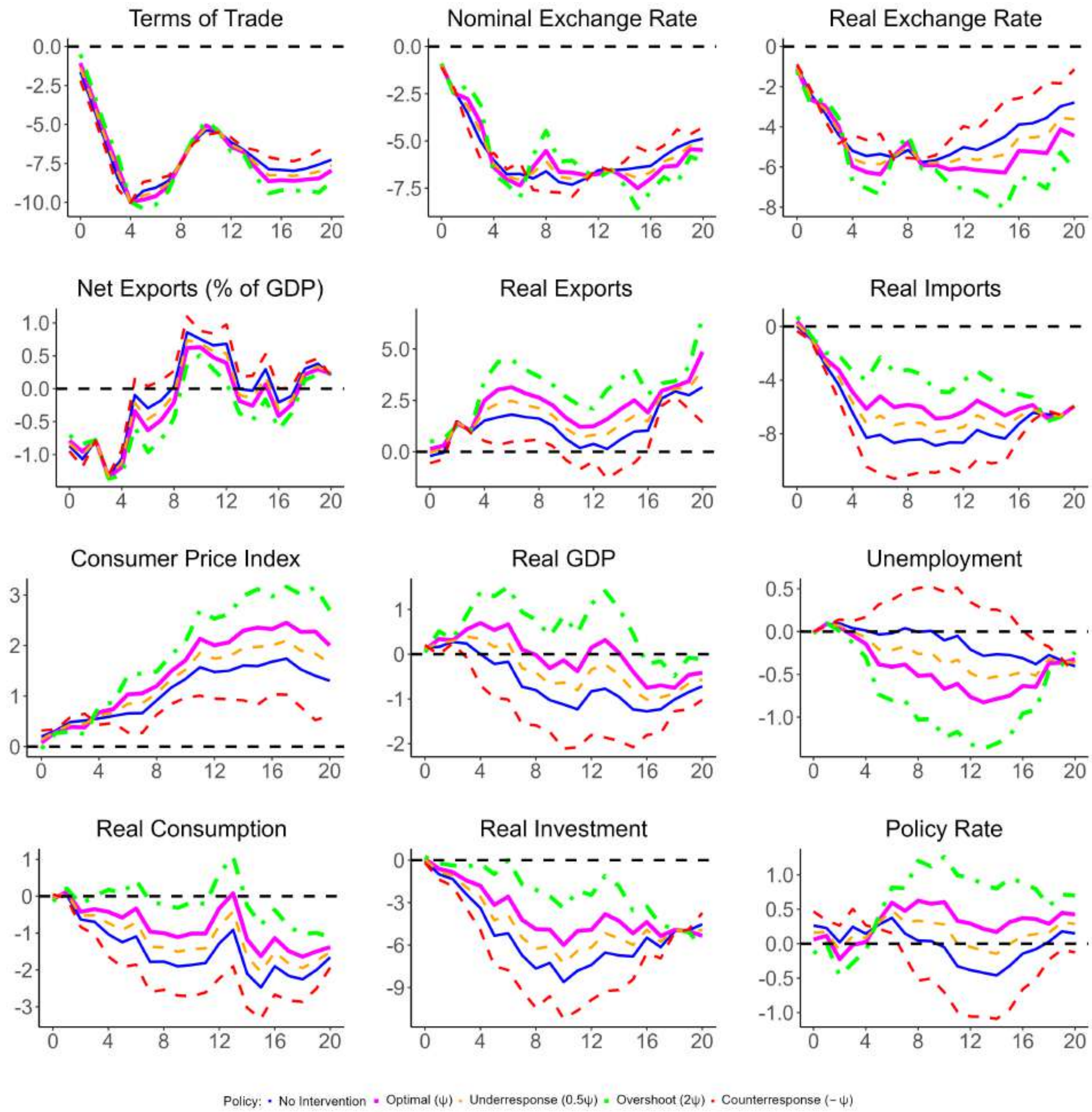

Figure B3: Counterfactual Impulse Responses to Different Policy Rules ($\lambda = 1$)

The plot shows the impulse responses of counterfactual policies on key macroeconomic variables. The model is estimated with $\lambda = 1$ and $\mathcal{H} = 20$. The blue thin solid line shows the dynamic effects under no response ($\psi = 0$). The magenta thick solid line shows the impulse responses under optimal intervention ($\psi = \hat{\psi}$). The red dashed line shows the impulse responses when the central bank adopts a policy on the opposite direction of the optimal ($\psi = -\hat{\psi}$). The green dotdash line shows the impulse responses when the central bank overresponds twice as much indicated by the optimal policy ($\psi = 2\hat{\psi}$). The orange dashed line shows the impulse responses when the central bank underesponds with half as much indicated by the optimal policy ($\psi = 0.5\hat{\psi}$).

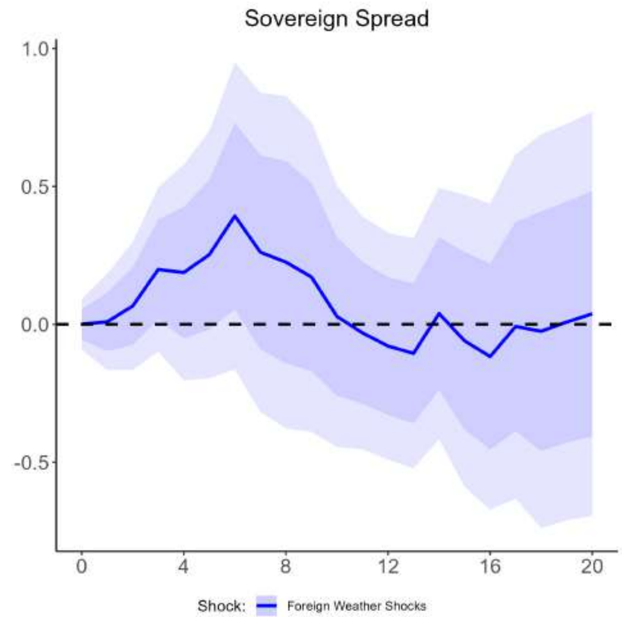

Figure B4: Response of Sovereign Spread to a Negative ToT Shock

The figure plots the IRF of sovereign spread (defined as the difference between long-term government bond yields and US government bond yields) to a negative ToT shock that causes a 10% fall of ToT 1 year forward. The IRFs are estimated with a panel local projections model 9 over 1980-2019 on economies for which OECD provides long-term bond yield data (see main text). The confidence intervals are estimated with country-clustered standard errors at the 68% and 90% level.

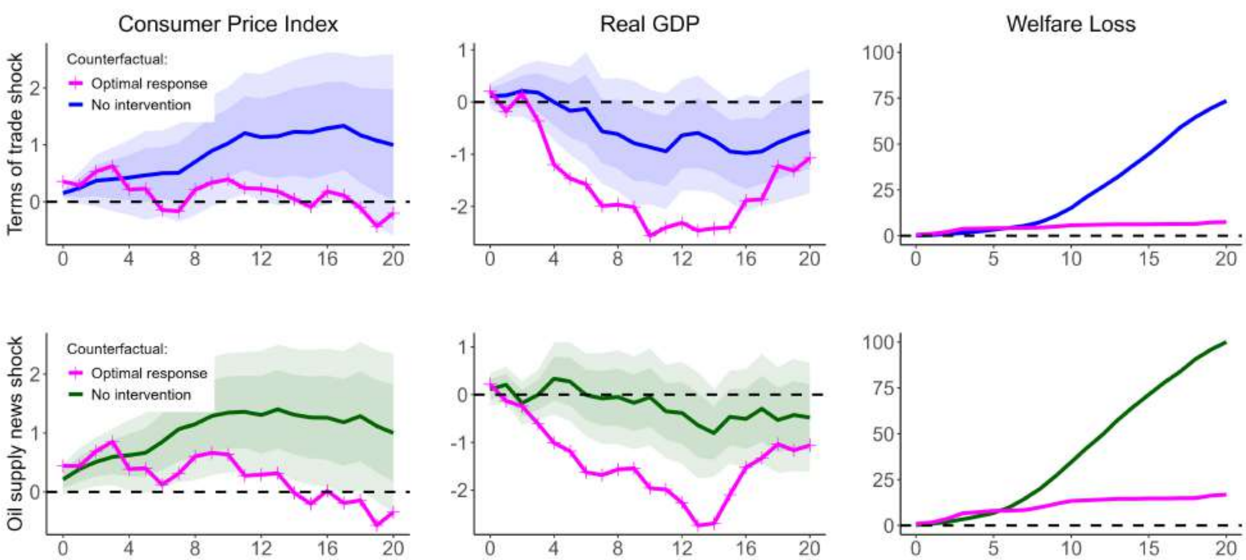

Figure B5: Comparison of ToT Shocks with Oil Supply News Shocks

The figure compares two counterfactuals produced for two different shocks: the ToT shocks and oil supply news shocks. The two shocks are scaled to cause a 1% cumulative inflation over a five-year horizon. The two counterfactuals are: the IRF under no intervention (solid blue line), and the IRFs under optimal monetary policy response (magenta line). The IRFs are estimated with a panel local projections model 9 over 1980-2019 (see main text). The welfare losses are all scaled using the five-year welfare loss of oil supply news shock under no intervention as baseline (100 units). The confidence intervals are estimated with country-clustered standard errors at the 68% and 90% level.

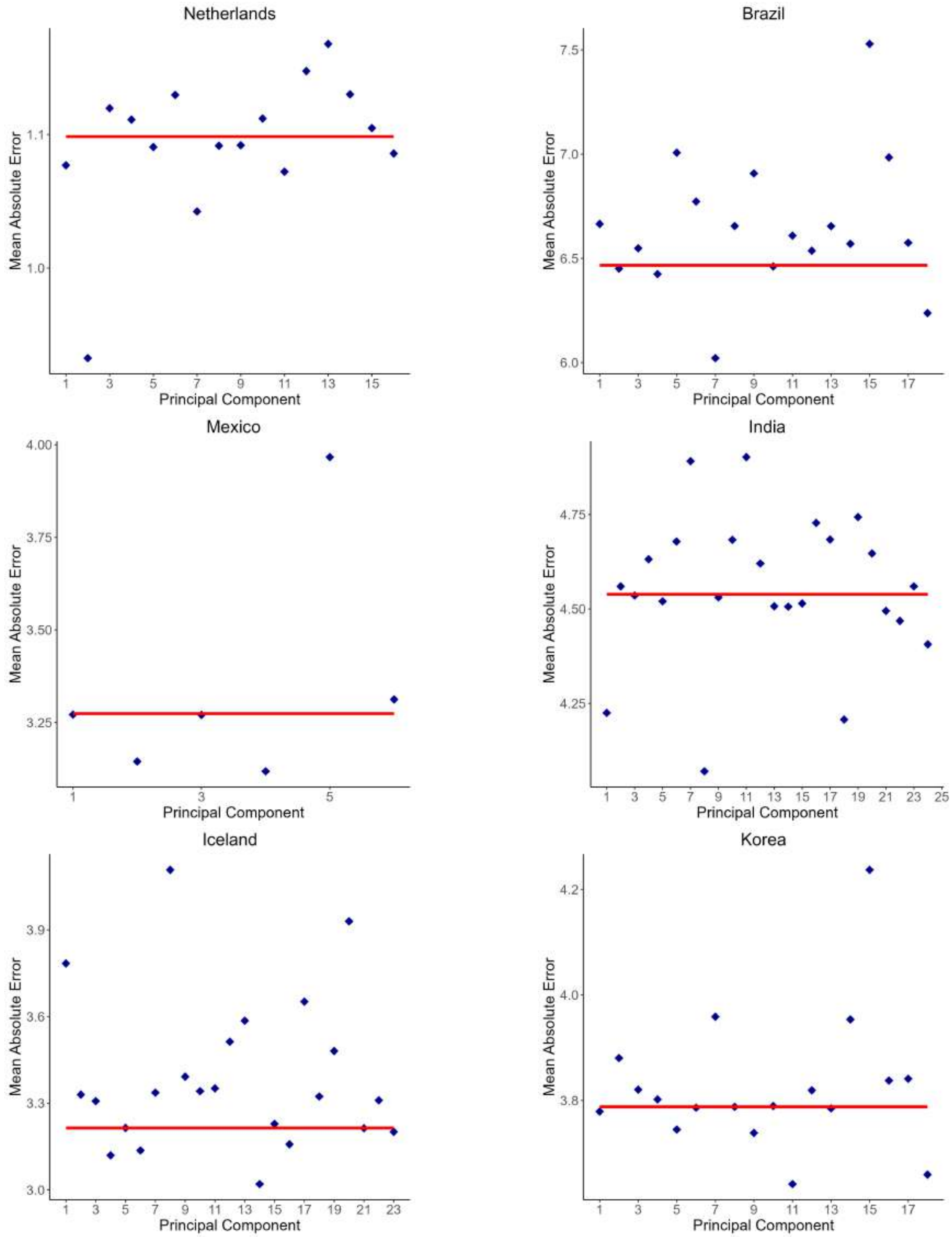

Figure B6: Principal Component Selection for Selected Countries

The plots show how principal components were selected for six countries: the Netherlands, Brazil, Mexico, India, Iceland and Korea. The principal components are arranged in descending order based on their eigenvalues. The **red**-colored straight line shows the median MAE of the baseline autoregressive model. Principal components with a smaller median MAE than the baseline model are characterized as powerful components and are included in the ToT instrument.

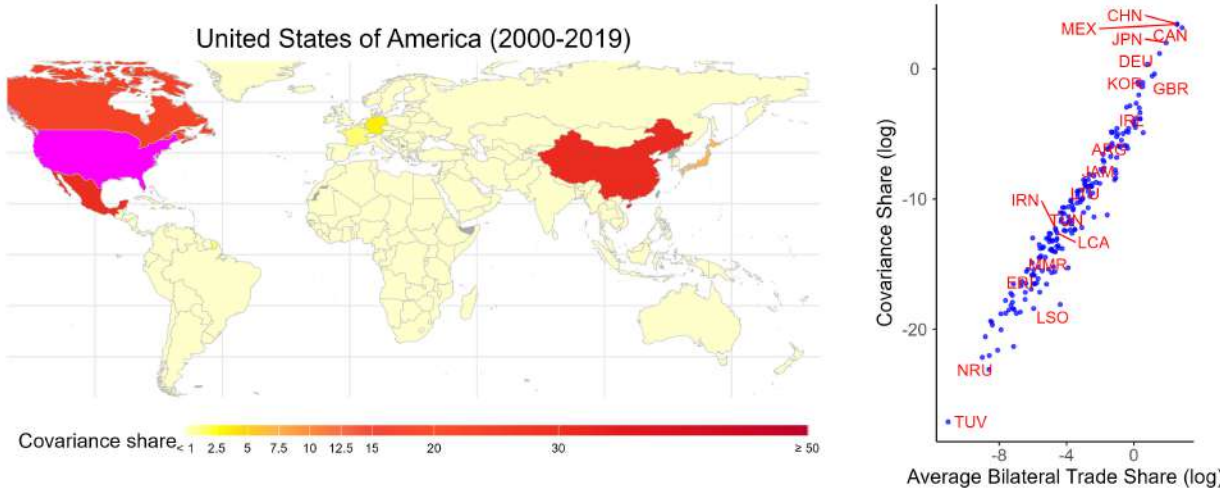

Figure B7: Instrument Decomposition by Country-origin in the United States

The figure maps the country-origin of terms-of-trade shocks in the USA attributed to foreign weather shocks over a 20-year window (2000-2019). The heatmap colors countries from yellow to red in ascending order of covariance share. Yellow color indicates covariance share below 1%. Dark gray color indicates no trade data with this country. Magenta color identifies the domestic economy. A scatter plot showing the positive relationship between the covariance share of equation (8) and the bilateral trade shares with trading partners during that window complements the map on the right.

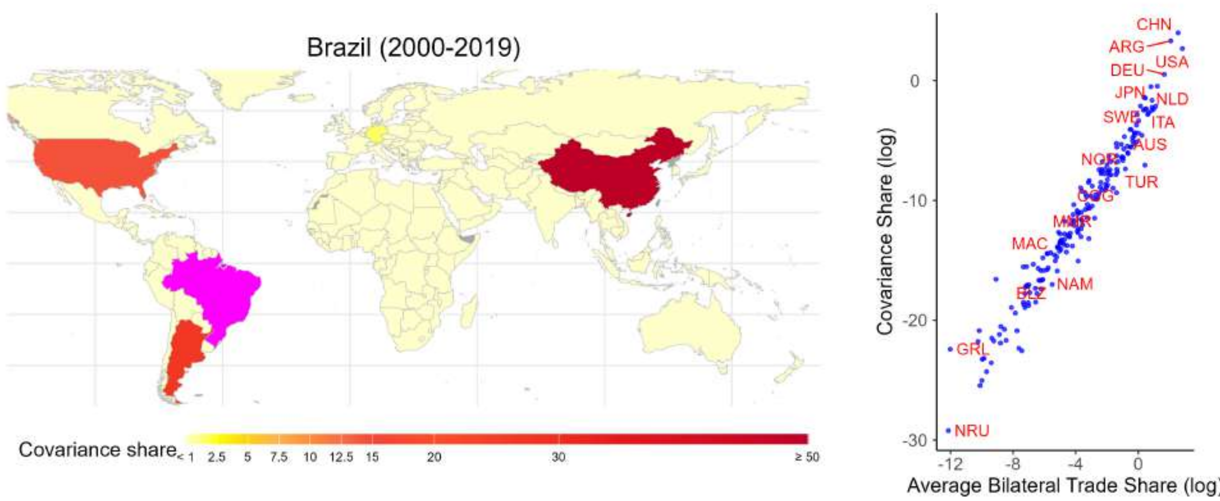

Figure B8: Instrument Decomposition by Country-origin in Brazil

The figure maps the country-origin of terms-of-trade shocks in Brazil attributed to foreign weather shocks over a 20-year window (2000-2019). The heatmap colors countries from yellow to red in ascending order of covariance share. Yellow color indicates covariance share below 1%. Dark gray color indicates no trade data with this country. Magenta color identifies the domestic economy. A scatter plot showing the positive relationship between the covariance share of equation (8) and the bilateral trade shares with trading partners during that window complements the map on the right.

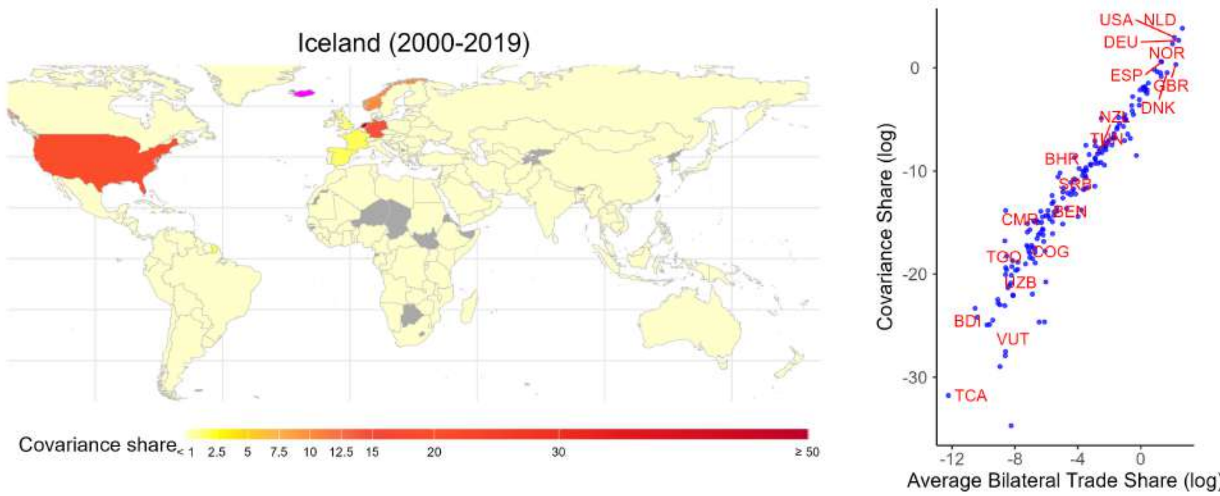

Figure B9: Instrument Decomposition by Country-origin in Iceland

The figure maps the country-origin of terms-of-trade shocks in Iceland attributed to foreign weather shocks over a 20-year window (2000-2019). The heatmap colors countries from yellow to red in ascending order of covariance share. Yellow color indicates covariance share below 1%. Dark gray color indicates no trade data with this country. Magenta color identifies the domestic economy. A scatter plot showing the positive relationship between the covariance share of equation (8) and the bilateral trade shares with trading partners during that window complements the map on the right.

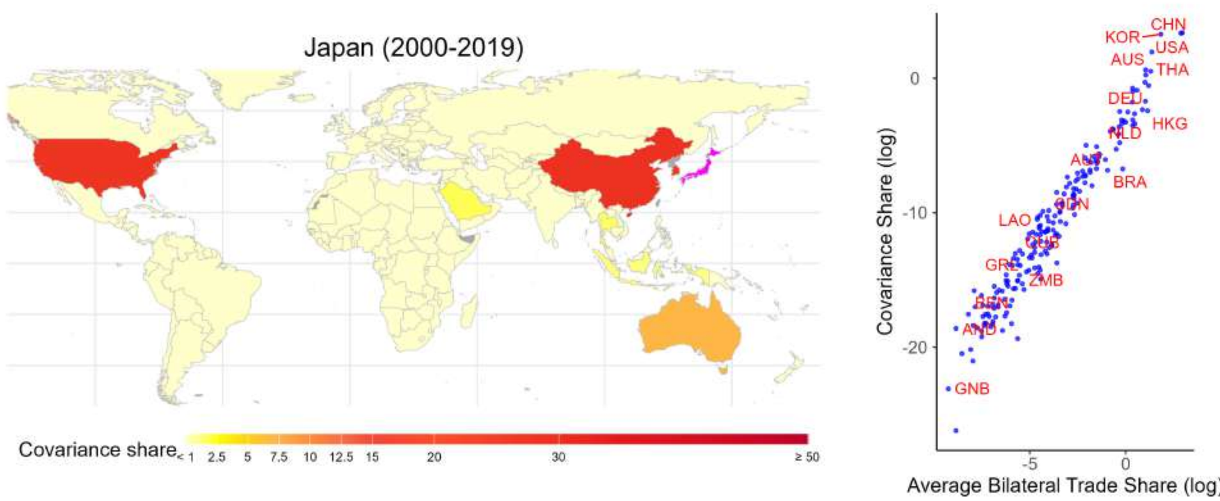

Figure B10: Instrument Decomposition by Country-origin in Japan

The figure maps the country-origin of terms-of-trade shocks in Japan attributed to foreign weather shocks over a 20-year window (2000-2019). The heatmap colors countries from yellow to red in ascending order of covariance share. Yellow color indicates covariance share below 1%. Dark gray color indicates no trade data with this country. Magenta color identifies the domestic economy. A scatter plot showing the positive relationship between the covariance share of equation (8) and the bilateral trade shares with trading partners during that window complements the map on the right.

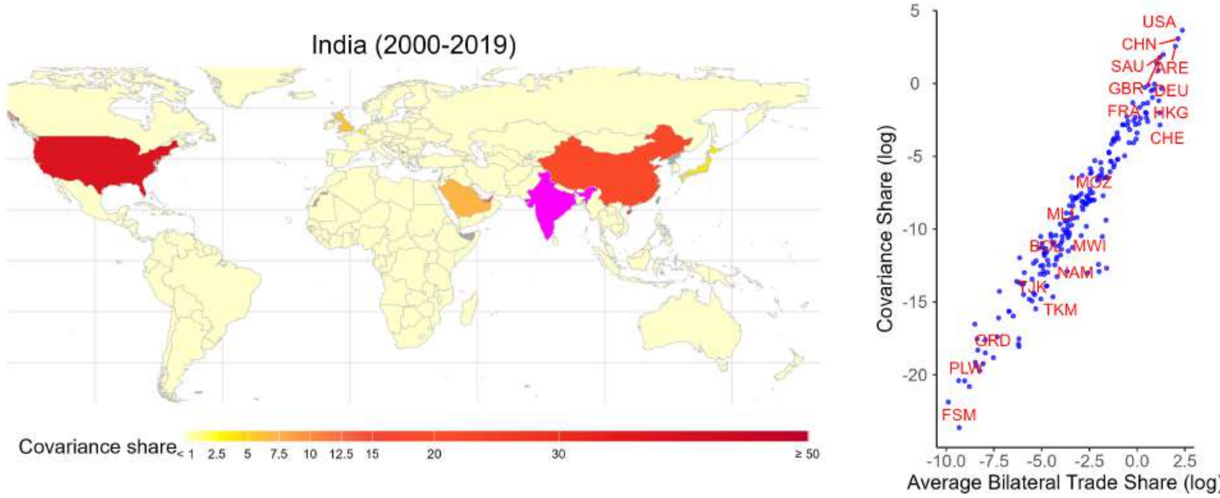

Figure B11: Instrument Decomposition by Country-origin in India

The figure maps the country-origin of terms-of-trade shocks in India attributed to foreign weather shocks over a 20-year window (2000-2019). The heatmap colors countries from yellow to red in ascending order of covariance share. Yellow color indicates covariance share below 1%. Dark gray color indicates no trade data with this country. Magenta color identifies the domestic economy. A scatter plot showing the positive relationship between the covariance share of equation (8) and the bilateral trade shares with trading partners during that window complements the map on the right.

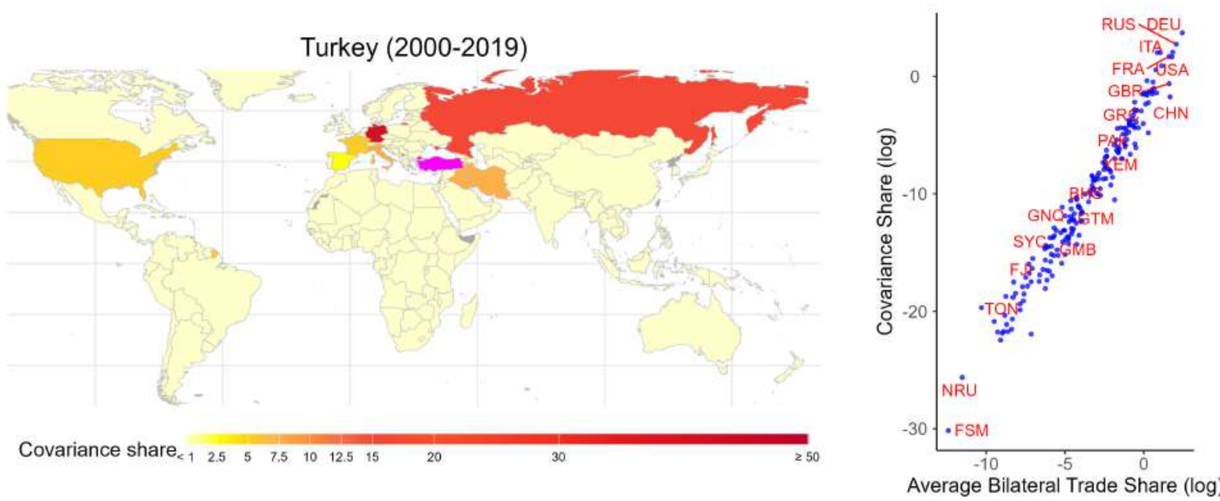

Figure B12: Instrument Decomposition by Country-origin in Turkey

The figure maps the country-origin of terms-of-trade shocks in Turkey attributed to foreign weather shocks over a 20-year window (2000-2019). The heatmap colors countries from yellow to red in ascending order of covariance share. Yellow color indicates covariance share below 1%. Dark gray color indicates no trade data with this country. Magenta color identifies the domestic economy. A scatter plot showing the positive relationship between the covariance share of equation (8) and the bilateral trade shares with trading partners during that window complements the map on the right.

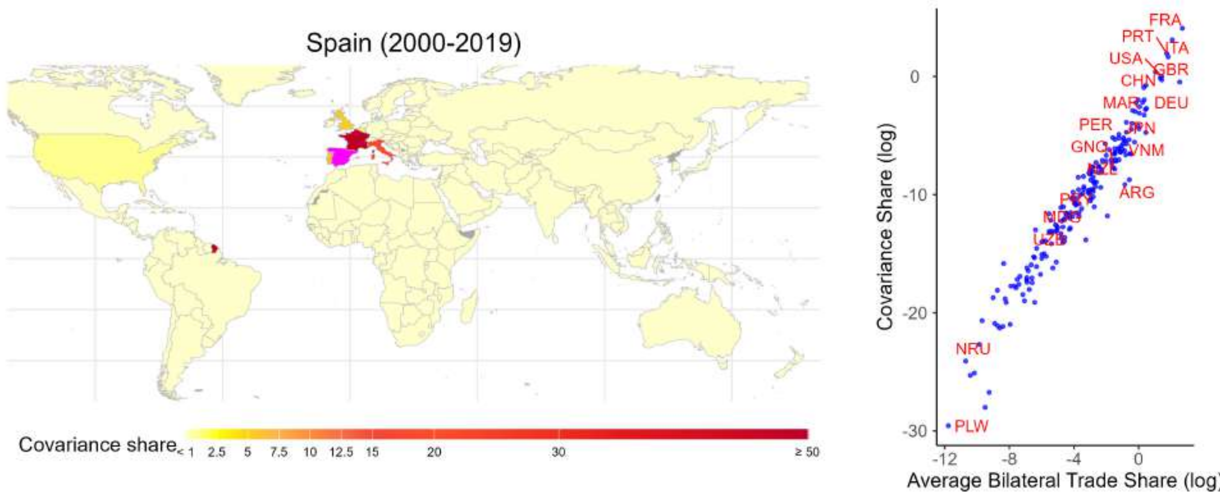

Figure B13: Instrument Decomposition by Country-origin in Spain

The figure maps the country-origin of terms-of-trade shocks in Spain attributed to foreign weather shocks over a 20-year window (2000-2019). The heatmap colors countries from yellow to red in ascending order of covariance share. Yellow color indicates covariance share below 1%. Dark gray color indicates no trade data with this country. Magenta color identifies the domestic economy. A scatter plot showing the positive relationship between the covariance share of equation (8) and the bilateral trade shares with trading partners during that window complements the map on the right.

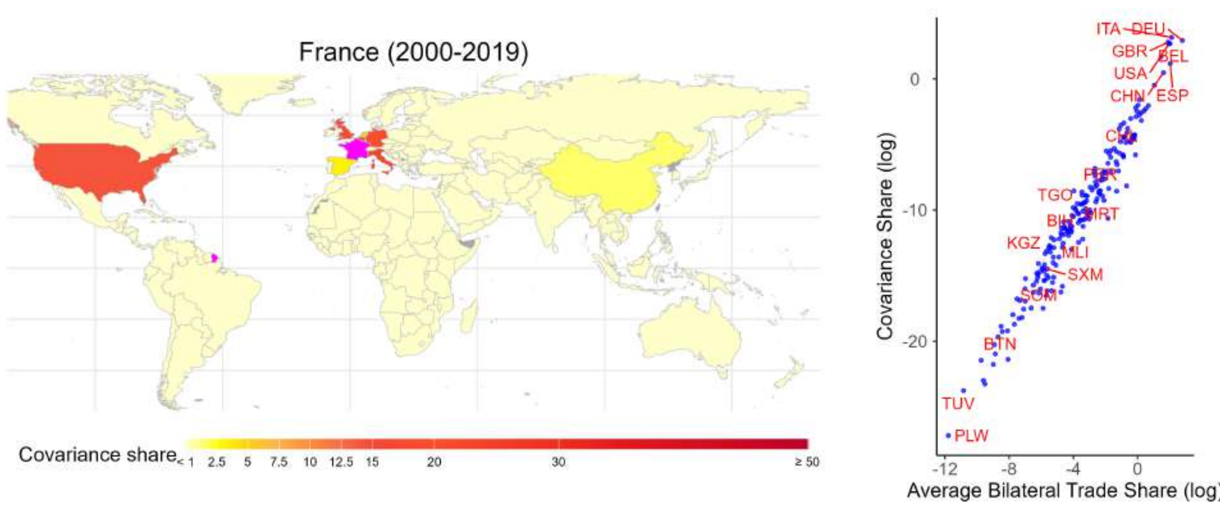

Figure B14: Instrument Decomposition by Country-origin in France

The figure maps the country-origin of terms-of-trade shocks in France attributed to foreign weather shocks over a 20-year window (2000-2019). The heatmap colors countries from yellow to red in ascending order of covariance share. Yellow color indicates covariance share below 1%. Dark gray color indicates no trade data with this country. Magenta color identifies the domestic economy. A scatter plot showing the positive relationship between the covariance share of equation (8) and the bilateral trade shares with trading partners during that window complements the map on the right.