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Threshold effects in exchange rate pass-through to food prices in emerging market economies

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Whether food price movements in emerging market economies are associated more closely with energy costs or exchange rate fluctuations is an important question for food security policy. This study examines this issue using a balanced monthly panel of 17 emerging market economies from January 2006 to December 2023. Country-specific cumulative pass-through coefficients are first estimated and then examined in relation to observable structural characteristics. State dependence is assessed using a threshold specification based on observed 12-month food inflation, complemented by quantile regressions across the conditional distribution. The results indicate considerable heterogeneity in exchange rate pass-through across countries. The mean cumulative coefficient is 0.213, with individual estimates ranging from −0.012 to 0.807. Pass-through also appears to vary with the inflation environment. Threshold estimates suggest a transition point between 6.8 and 7.6 percent annual food inflation, above which the response of food prices to exchange rate movements tends to become stronger. Within-country mean-group estimates provide further support for this interpretation, suggesting that the observed regime differences are not solely attributable to country composition. The estimated effect is higher in the high-inflation state in all eight economies for which both states can be reliably estimated. By comparison, the cumulative effect of crude oil prices is modest: 0.008 over 6 months, which is not statistically distinguishable from zero, rising to 0.064 over 18 months and becoming statistically detectable. The results do not provide consistent evidence of comparable state dependence in either the energy price or global commodity price channel. Similarly, structural indicators such as food import dependence, energy dependence, and fertilizer import dependence do not appear to account systematically for cross-country variation in pass-through. Overall, the findings suggest that exchange rate movements may play a relatively greater role in consumer food price dynamics than energy price movements in the emerging market economies considered, particularly during periods of elevated food inflation. The results also suggest that macro-financial stability may be relevant for food price stabilization and that the effectiveness of trade-based policy measures may depend on the relative importance of exchange rate transmission.

KEYWORDS
state dependence, inflation regimes, food security, currency depreciation, oil prices

1 Introduction

Over the past two decades, the formation of food prices has become a problem that transcending the dynamics of agricultural supply and demand. Climate change, geopolitical tensions, and global pandemics have created a complex crisis environment by leading to supply chain disruptions. In particular, food security has ceased to be the sole focus of traditional agricultural policies and has become a crucial component of macroeconomic stability. Goal 2.c of the United Nations Sustainable Development Target underscores this shift by explicitly defining the proper functioning of food commodity markets and the limitation of extreme food price volatility as a policy objective (United Nations, 2017). Progress towards this target is monitored through indicator 2.c.1, the indicator of food price anomalies, which FAO computes from nationally reported food consumer price indices (FAO, 2026a) the same class of series analysed here.

The welfare implications of price volatility are particularly pronounced in emerging market economies. For instance, in Turkiye, food expenditures account for approximately 18–20 percent of household budgets, constituting the third largest expenditure item after housing and transportation (TURKSTAT, Turkish Statistical Institute, 2025). This share is even higher for low-income households; therefore, fluctuations in food prices generate a distinct and more severe welfare impact compared to overall inflation. Rising food prices are known to be associated not only with economic consequences, such as declining production and rising costs, but also with social unrest (Bellemare, 2015). OECD/FAO (2023) projections also indicate that a 1 percent increase in fertilizer prices could lead to a 0.2 percent distortion in agricultural commodity prices. It is estimated that a 25 percent increase in the prices of nitrogen, phosphorus, and potassium fertilizers could push this effect up to 5 percent.

The dependence of modern agriculture on energy-intensive inputs, such as fuel and fertilizer, establishes a direct link between oil prices and food costs (Gilbert, 2010; Nazlioglu and Soytas, 2012). The expansion of biofuel policies has structurally deepened this connection (Mitchell, 2008; Harri et al., 2009), and it has been estimated that increases in oil prices are transmitted to food prices at an average rate of 17 percent (Baffes, 2007). However, another perspective argues that energy prices play a relatively limited role in determining food costs (Baumeister and Kilian, 2014), while some studies suggest that the relationship between food and oil prices can be neutral under certain conditions (Reboredo, 2012). This divergence in findings is thought to stem from the structural characteristics and levels of external dependence of the countries examined.

In emerging market economies, however, the center of gravity for price formation shifts from the energy market to the foreign exchange market. In these economies, the exchange rate serves as a nominal anchor for domestic prices, and local currency depreciation rapidly increases the costs of imported fertilizers, seeds, and fuel (Baek and Koo, 2010; Kayamo, 2021; Tümtürk, 2026). High levels of exchange rate pass-through (ERPT) have been observed even in economies implementing inflation targeting (Nasir et al., 2020). The question that arises here is whether food inflation in particularly fragile economies is primarily triggered by energy shocks or exchange rate shocks.

Taylor (2000) argued that pass-through is not a constant structural parameter; rather, firms' propensity to pass cost increases onto prices depends on the prevailing inflation environment. In an environment with low inflation and anchored expectations, firms perceive cost shocks as temporary and delay price adjustments. Conversely, in an environment where inflation is perceived as high and persistent, the same shock is rapidly and almost entirely passed on to the consumer. This insight requires that pass-through be measured not by a single average coefficient, but separately according to the inflation environment.

In the literature, the majority of ERPT studies focus on the overall consumer price index, whereas food-specific pass-through is addressed in a limited number of studies. The weight of food in household budgets and its reliance on imported inputs necessitate a separate analysis of this item. The literature on the energy-food nexus predominantly utilizes global commodity indices, and there are few studies that jointly model domestic consumer prices and the exchange rate channel. Another key aspect is the inclusion of state dependence within this joint framework. The contribution of this study is to integrate these three dimensions within an empirical framework and to measure how pass-through to food prices varies according to the inflation regime.

The analysis relies on a balanced panel dataset of 17 emerging market economies at a monthly frequency covering the period from 2006:01 to 2023:12. The empirical strategy combines four complementary analyses. First, separate distributed lag models are estimated for each country to obtain country-specific cumulative pass-through coefficients. Second, these country-specific estimates are related to observable structural characteristics in a cross-sectional framework. Third, an explicit threshold approach uses the actual inflation rate experienced by each economy to test whether pass-through differs between low- and high-inflation environments. Fourth, quantile regressions with country fixed effects characterize how pass-through varies across the conditional distribution of food inflation.

The findings differ from initial expectations in three respects. First, the cumulative effect of oil prices on consumer food prices is considerably smaller than that of exchange rate movements across all horizons examined. There is also little evidence that oil price pass-through varies systematically with the inflation environment. These results provide limited support for the commonly assumed central role of energy prices in shaping domestic consumer food prices. However, the effect is not absent, as it becomes statistically detectable when the time horizon extends beyond 1 year. Second, exchange rate pass-through appears to depend on the inflation environment in a nonlinear manner. It remains relatively stable at moderate levels of inflation but increases more noticeably once inflation moves beyond this range. A mean-group estimator based on within-country variation provides further support for this pattern. The results suggest that the observed relationship reflects changes in pass-through across inflation states within countries rather than simply a concentration of high-inflation episodes in economies that generally exhibit stronger pass-through. Third, the findings do not provide clear support for the expectation that the relationship between global food prices and domestic prices weakens during periods of elevated inflation. At the same time, there is no consistent evidence that this relationship strengthens under such conditions. After accounting for the fact that global food prices represent a common external factor across countries, no reliable evidence of regime dependence is identified for this channel. Taken together, the results suggest that the response to the inflation environment differs across external price transmission channels. In particular, exchange rate pass-through appears to strengthen during periods of higher inflation, while comparable changes are not consistently observed for oil or global food prices. These findings suggest that state dependence in domestic food price transmission may be more closely associated with the exchange rate channel than with external price pressures in general.

In this study, cross-country differences in pass-through cannot be explained by observable structural indicators such as food import dependence, energy dependence, or fertilizer import dependence. This result suggests that the explanation should be sought in within-country regime shifts rather than structural differences across countries, thereby complementing the main finding of the study.

These findings have direct policy implications. If the primary source of food inflation is the exchange rate channel, trade restrictions and export bans act as misguided policy levers; such tools can reduce producer incomes and lead to a contraction in supply in the medium term. Indeed, SDG Target 2.c aims to limit extreme volatility in food prices by ensuring the proper functioning of food markets. The finding of state dependence in this study provides an additional implication for this objective. The fact that cost pass-through strengthens and triggers price anomalies in a high-inflation environment demonstrates that maintaining stability in pricing behavior is essential not only for overall macroeconomic stability but also directly for the predictability and accessibility of food markets.

The remainder of this study is structured as follows. Section 2 presents the conceptual framework and formulates the hypotheses. Section 3 introduces the data and methodology. Section 4 reports the empirical findings. Section 5 discusses the results and concludes with policy implications.

2 Conceptual framework

2.1 The energy-food nexus

The role of energy costs in the formation of food prices stems from the structural characteristics of agricultural production. Fuel and fertilizer constitute a significant portion of production costs, while transportation and cold chain costs are reflected in every stage the product undergoes from farm to consumer. Therefore, the view that movements in oil prices are transmitted to agricultural commodity prices is widely accepted in the literature (Gilbert, 2010; Nazlioglu and Soytas, 2012). While it is estimated that increases in oil prices are passed through to food prices at an average rate of 17 percent (Baffes, 2007), it has been emphasized that this relationship poses a risk not only to energy markets but also directly to food security (Taghizadeh-Hesary et al., 2019).

The expansion of biofuel policies has structurally deepened this nexus. The diversion of an increasing share of agricultural products to energy production has linked these two markets on the demand side as well (Mitchell, 2008; Harri et al., 2009; Su et al., 2019). It is also known that this link strengthens during crisis periods and that oil price increases leave a more persistent impact on food markets than price decreases do (Cheng and Cao, 2019; Karakotsios et al., 2021; Alnour et al., 2023; Cao et al., 2023). The fertilizer channel constitutes the second pillar of this relationship; Alexander et al. (2023) and Vos et al. (2025) demonstrate that increases in fertilizer prices directly raise marginal production costs. Ott (2012), on the other hand, points out that the relationship can be bidirectional, where rising food demand increases fertilizer demand, and the resulting cost increase feeds back into food prices.

Contrary findings also exist; while it is argued that energy prices play a relatively limited role in determining food costs (Baumeister and Kilian, 2014), some studies suggest that the relationship may be neutral under certain conditions (Reboredo, 2012). A major reason for this divergence in findings may be that most studies rely on global commodity indices. Even if the relationship between global food commodity prices and oil prices is strong, the extent to which this relationship is transmitted to domestic consumer prices is a separate question. Retail food prices also incorporate processing, packaging, distribution, rent and labour costs, leaving the raw commodity component with a limited share of the total. In the United States, the farm share of the consumer food dollar was 11.8 cents in 2024, with the remaining 88.2 cents accruing to post-farm activities; energy enters as one of 12 supply-chain industry groups rather than as a dominant cost (USDA ERS, 2026).

2.2 The exchange rate pass-through channel

In emerging market economies, the center of gravity for price formation lies in the foreign exchange market, and the exchange rate serves as a de facto nominal anchor for domestic prices (Kayamo, 2021). When this macroeconomic dynamic is examined specifically for agriculture, local currency depreciation directly increases the costs of essential production inputs such as imported fertilizers, seeds, agrochemicals, and fuel (Baek and Koo, 2010). The effect is not limited to imported inputs: the domestic price of tradable agricultural products is determined by the local currency equivalent of the world price; consequently, depreciation also drives up the domestic prices of exportable goods.

Pass-through to import prices has been shown to be high in a heterogeneous panel of West African countries (Kinda and Barry, 2021). Significant pass-through levels have also been detected in small open economies implementing inflation targeting (Nasir et al., 2020). The role of food prices in inflation dynamics has been demonstrated in an agriculture-based economy (Loening et al., 2009); similar findings in this area have been confirmed across different country groups as well (Mishra et al., 2024).

2.3 Food-specific pass-through

The majority of the literature focuses on the overall consumer price index. There are two reasons that necessitate a separate examination of food-specific pass-through. First, the import input intensity and the degree of tradability of the food basket differ from other items. Second, and crucial from a welfare perspective, the weight of food in household budgets is much higher for low-income households, and higher again in lower-income economies: food accounted for more than 40 percent of total consumer expenditure in low-income African and South Asian countries in 2022, against less than 10 percent in the United States and the United Kingdom (USDA ERS, 2023). This makes a movement in food prices distributionally more significant than a general price movement of the same magnitude (Bellemare, 2015).

2.4 State dependence: the Taylor hypothesis

The assumption that pass-through is a constant structural parameter is theoretically difficult to defend. Taylor (2000) posited that firms' propensity to pass cost increases onto prices depends on the prevailing inflation environment. The basis of the argument relates to pricing power and expectations: in an environment where inflation is low and expectations are anchored, firms perceive cost shocks as temporary, delay adjustments in anticipation that competitors will not raise

prices, and absorb part of the shock through their profit margins. Conversely, in an environment where inflation is perceived as high and persistent, this situation is reversed, and the cost increase is rapidly and almost entirely passed on to the consumer. The state dependence hypothesis has been empirically tested, revealing a positive and significant relationship between pass-through and the average inflation rate (Choudhri and Hakura, 2006).

This pass-through should be measured not by a single average coefficient, but separately at different points of the conditional distribution. Because high inflation periods remain a minority within the sample, estimators based on the conditional mean systematically underrepresent the behavior during these periods.

Two empirical strategies are available, and they capture distinct dimensions of the relationship. The first defines the inflation regime directly using the actual inflation rate experienced by each economy and tests whether pass-through differs across states, providing a closer analogue to the mechanism described by Taylor. The second estimates pass-through at different points across the conditional distribution of food inflation. Quantile regression is well suited for this second purpose and offers the distinct advantage of utilizing the entire sample rather than relying solely on the minority of observations that fall into a high-inflation state. However, the quantiles it identifies are conditional: they isolate months in which inflation is elevated relative to what covariates predict, which is conceptually distinct from periods of objectively high inflation. This study therefore employs both methods, treating the threshold specification as the primary test of state dependence.

While this state-dependent dimension has been tested for overall consumer prices in the literature, it has been examined to a limited extent specifically for food prices. Food is one of the indicators where state dependence is most strongly expected, as it exhibits a high frequency of price adjustments, a heterogeneous product group, a large number of intermediaries, and low price elasticity of demand on the consumer side. These characteristics facilitate the acceleration of cost transmission in environments of rising inflation.

The non-linear nature of exchange rate pass-through and its sensitivity to macroeconomic instability regimes align with findings in the broader literature. For instance, exchange rate pass-through has been shown to increase significantly once inflation volatility crosses a specific threshold of 4.17 (Soon et al., 2018). This observation aligns closely with the analytical results of the study regarding the rise in the cumulative pass-through coefficient once annual food inflation surpasses the 15%. Similarly, empirical evidence confirms that the impact of commodity price shocks on domestic inflation is substantially more pronounced in countries with higher initial inflation, reinforcing the state-dependent framework of the study (Gelos and Ustyugova, 2017). In a related context, exchange rate movements have also been found to exert a significant transmission effect on food inflation under high-uncertainty regimes (Balcilar and Usman, 2026). However, while Balcilar and Usman (2026) highlight uncertainty in global energy markets as the primary threshold variable triggering pass-through (at a threshold level of 38.51%), the analysis conducted in this study finds that the cumulative impact of oil prices on consumer food prices is small and does not vary systematically with the inflation regime. In the present model, the principal factor triggering pass-through is the level of the domestic inflation environment itself. Conversely, while the study finds that pass-through increases during elevated inflation periods in line with the theoretical framework suggesting that low inflation environments constrain firm pricing power (Taylor, 2000), contrasting evidence also exists in the literature. For example, exchange rate pass-through has been reported to be higher in Sub-Saharan African economies characterized by lower inflation and lower volatility compared to their higher-volatility developing counterparts (Kassi et al., 2019).

2.5 Cross-country heterogeneity

It is expected that pass-through varies across countries, and the literature generally relies on structural exposure indicators to explain these differences. It is anticipated that in economies with high food import dependence, exchange rate shocks will affect a broader portion of the consumer basket; in energy-importing economies, the input cost channel will operate more strongly; and producers reliant on fertilizer imports will pass on cost increases more rapidly. This expectation rests on the assumption that structural exposure is the primary determinant of pass-through. Indeed, pass-through is observed more intensely as import dependence in production increases (Mazorodze, 2026).

Testing this assumption requires that pass-through coefficients be estimated separately at the country level. Because pooled estimators produce a single average coefficient, they are inherently incapable of answering questions regarding cross-country variation. For this reason, a two-stage design is adopted in this study; in the first stage, country-specific cumulative pass-through coefficients are obtained, and in the second stage, the relationship between these coefficients and country characteristics is examined.

2.6 Hypotheses

The discussion above yields four testable hypotheses.

H1. The exchange rate channel dominates the oil channel in determining consumer food prices. Because the exchange rate simultaneously affects both imported input costs and the domestic prices of tradable goods in emerging market economies, its cumulative impact is expected to be larger than that of oil.

H2. Exchange rate pass-through is state-dependent and is higher in high-inflation environments. Following Taylor (2000), this relationship need not be linear in the inflation rate: actors along the agrifood supply chain may absorb cost shocks into their margins across a broad range of moderate inflation, altering their pricing behavior only when inflation becomes sufficiently high to be perceived as persistent. The hypothesis is therefore tested using both an explicit threshold approach and across the conditional distribution.

H3. The link between global food prices and domestic food prices weakens in a high-inflation regime. During crisis periods, it is expected that domestic dynamics, particularly exchange rate shocks, will dominate price formation, while the connection with global markets will recede into the background. This hypothesis is directional, and the analysis below rejects it in the stated form without supporting its converse.

H4. Cross-country differences are associated with observable structural exposure indicators (food import dependence, energy dependence, fertilizer import dependence).

3 Materials and methods

3.1 Data and sample

This study relies on a balanced panel of 17 emerging market economies at a monthly frequency, covering the period from 2006:01 to 2023:12. The panel comprises 216 time observations and a total of 3,672 country-month observations, with no missing values in the series.

The determination of the sample boundary at 2023:12 stems from a data-related constraint: the exchange rate series in the International Monetary Fund's International Financial Statistics database ends on this date, and the objective was to obtain a balanced panel without resorting to interpolation.

The selection of countries is based on four criteria. First, the economy is classified as an emerging market by either the MSCI Emerging Markets Index (MSCI, 2026) or by the International Monetary Fund's World Economic Outlook grouping of emerging market and developing economies (IMF, 2023). Second, the economy does not operate a pegged or crawling peg arrangement, which excludes Vietnam, Morocco, and Saudi Arabia, as well as China due to its managed peg combined with extensive capital account restrictions throughout most of the sample period. Third, the economy does not maintain centrally administered or regulated consumer food prices during the sample period, as such interventions sever the transmission mechanism between import costs and the retail price index. Fourth, complete monthly data are available for all series across the entire period. Crucially, none of the selection criteria condition on the realized behavior of inflation or food prices (Figure 1).

The resulting sample comprises five economies from Latin America (Brazil, Chile, Colombia, Mexico, Peru), five from Asia (India, Indonesia, the Philippines, Thailand, Malaysia), and seven from Europe, the Middle East, and Africa (EMEA) region (Poland, Hungary, Romania, Czechia, Kazakhstan, Turkiye, South Africa). Achieving this regional balance is important to demonstrate that the findings are not specific to a single geographic region.

3.2 Variables

The dependent variable is the food consumer price index (CPI) published by FAOSTAT (FAO, 2026b). The use of a food-specific index rather than the overall consumer price index is directly aligned with the focus of this study: because the share of food expenditure in household budgets is disproportionately high in emerging market economies, movements in food prices exert a distinct impact on welfare compared to overall inflation. The explanatory variables are presented in Table 1.

In addition to these variables, three time-invariant country-level exposure indicators are used: the ratio of net energy imports to energy use, the share of food imports in total merchandise imports, and the ratio of fertilizer imports to agricultural use (Table 2). These indicators are included as explanatory variables in the cross-country cross-sectional analysis; however, because they do not vary over time, they are excluded from the main model.

Table 3 reports these indicators by country alongside each economy's mean annual food inflation and the number of months spent above the 15% threshold, so that the exposure measures can be read against the inflation environment in which each economy operated.

3.3 Preliminary tests

Prior to the selection of the estimator, three properties of the panel are examined. Pesaran's CD test (Pesaran, 2004), the Friedman test, and the Breusch-Pagan LM test are applied to check for cross-sectional dependence. Slope homogeneity is tested using Swamy's S statistic (Swamy, 1970), which is directly calculated as the quadratic form of the deviations of country-specific slope vectors from the weighted fixed effects estimator.

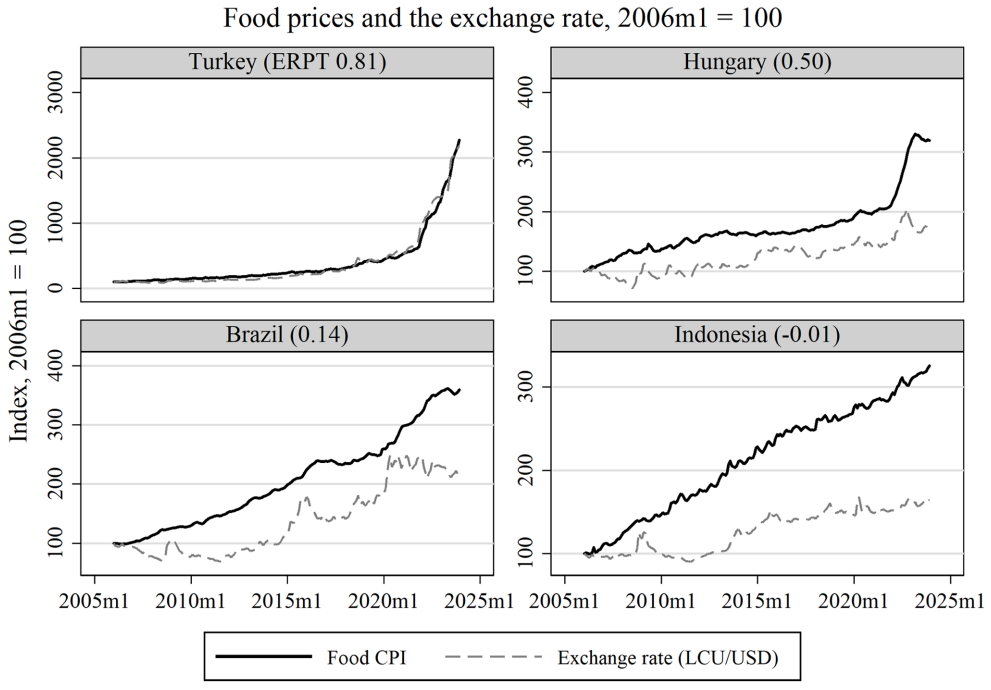


FIGURE 1
Food CPI and nominal exchange rate in selected countries, January 2006 = 100.

TABLE 1 List and description of variables.

Variable	Definition	Source	Transformation
FoodCPI[1]	Consumer price index, food, monthly, 2015 = 100	FAOSTAT	Log first difference
ExRate[2]	Nominal exchange rate, LCU per USD, period average	IMF IFS	Log first difference
ExRate_eop	Nominal exchange rate, end of period (robustness)	IMF IFS	Log first difference
Brent[3]	Brent crude oil spot price, USD per barrel	FRED	Log first difference
FAO[4]	FAO Food Price Index, 2014–2016 = 100	FAO	Log first difference
Urea[5]	Urea fertilizer price, USD per tonne	World Bank Pink Sheet	Log first difference
EnergyDep[6]	Net energy imports as share of energy use, 2006–2015 mean	World Bank WDI	Time-invariant
FoodImpDep[7]	Food imports as share of merchandise imports, 2006–2023 mean	World Bank WDI	Time-invariant
FertDep[8]	Fertilizer imports relative to agricultural use, capped at 1.5	FAOSTAT fertilizers by nutrient	Time-invariant
GPR[9]	Country geopolitical risk index (robustness, 14 countries)	Caldara and Iacoviello (2022)	log(1 + GPR)
Crisis	Dummies: GFC 2008 m9-2009 m6, COVID 2020 m3-2021m12, war from 2022 m2	Author construction	Binary

[1]FAO. Consumer Price Indices. FAOSTAT. Available at: https://www.fao.org/faostat/en/#data/CP [Accessed June 20, 2026].
[2]International Monetary Fund. International Financial Statistics. Available at: https://data360.worldbank.org/en/dataset/IMF_IFS [Accessed June 20, 2026].
[3]Federal Reserve Bank of St. Louis. Global price of Brent Crude (MCOILBRENTEU). FRED. Available at: https://fred.stlouisfed.org/series/MCOILBRENTEU [Accessed July 2, 2026].
[4]FAO. FAO Food Price Index. Available at: https://www.fao.org/worldfoodsituation/foodpricesindex/en/ [Accessed June 20, 2026].
[5]World Bank. Commodity Markets: Pink Sheet. Available at: https://www.worldbank.org/en/research/commodity-markets [Accessed June 15, 2026].
[6]World Bank. Energy imports, net (% of energy use), World Development Indicators. Available at: https://data.worldbank.org/indicator/EG.IMP.CONS.ZS [Accessed June 17, 2026].
[7]World Bank. Food imports (% of merchandise imports), World Development Indicators. Available at: https://data.worldbank.org/indicator/TM.VAL.FOOD.ZS.UN [Accessed June 16, 2026].
[8]FAO. Fertilizers by Nutrient. FAOSTAT. Available at: https://www.fao.org/faostat/en/#data/RFN [Accessed June 19, 2026].
[9]Data available at: https://www.matteoiacoviello.com/gpr.htm [Accessed June 16, 2026].

The order of integration is determined using the Pesaran CIPS test (Pesaran, 2007), which remains valid under cross-sectional dependence; for global series lacking cross-sectional variance, the augmented Dickey-Fuller (ADF) test is employed. Cointegration is examined using Westerlund's error-correction-based panel tests (Westerlund, 2007).

Second-generation panel unit root tests are employed because cross-sectional dependence is pervasive across these series. For the levels of food consumer prices, the Pesaran CD statistic is 163.37 with an average pairwise correlation of 0.95, which invalidates first-generation panel tests that assume cross-sectional independence. The global series present a distinct methodological issue. Because oil, urea, and the FAO index take identical values across all countries in any given month, their cross-sectional variance is zero and panel unit root tests cannot be defined for them. Consequently, these series are evaluated individually using Augmented Dickey-Fuller regressions.

3.4 Empirical strategy

3.4.1 Justification for first differences

The model is specified in first differences, a choice motivated by three main reasons. First, the CIPS test fails to reject the unit root hypothesis for both food prices and the exchange rate, and the evidence regarding cointegration remains sensitive to model specification. Consequently, estimation in levels introduces the risk of spurious regression. Second, pass-through is inherently a relationship of rates of change; it represents the transmission rate of a percentage change in the exchange rate to a percentage change in prices. Third, the first-difference specification aligns with standard pass-through models in the literature, thereby enhancing the comparability of the estimated coefficients. Indeed, previous studies have similarly concluded an absence of cointegration based on Westerlund's panel cointegration tests, subsequently estimating the pass-through equation in first differences (Cheikh and Louhichi, 2016).

3.4.2 Country-specific distributed lag model

A separate time series regression is estimated for each country:

$$\Delta lnFoodCPI_{it} = \alpha_i + \sum_{j=0}^{12} \beta_{ij} \Delta lnExRate_{i,t-j} + \sum_{j=0}^{6} \gamma_{ij} \Delta lnBrent_{t-j} + \sum_{j=0}^{6} \delta_{ij} \Delta lnFAO_{t-j} + \sum_{j=0}^{6} \theta_{ij} \Delta lnUrea_{t-j} + \varepsilon_{it} \quad (1)$$

TABLE 2 Descriptive statistics for 17 emerging market economies, January 2006–December 2023.

Descriptive statistics						
Variables	Count	Mean	SD	Min	p50	Max
Food CPI (2015 = 100)	3,672	104.177	51.682	40.168	99.600	913.709
Exchange rate (LCU per USD)	3,672	943.568	2894.749	1.172	21.968	15,867.432
Brent crude (USD/barrel)	3,672	77.072	24.730	18.380	73.960	132.720
Urea (USD/tonne)	3,672	332.273	149.435	142.600	285.650	925.000
FAO Food Price Index	3,672	107.774	19.106	69.800	100.900	160.200
Food inflation (% m/m)	3,655	0.523	1.137	−8.584	0.395	14.833
Depreciation (% m/m)	3,655	0.280	2.857	−15.179	0.049	25.423
Brent growth (% m/m)	3,655	0.097	10.991	−55.479	1.630	46.905
FAO index growth (% m/m)	3,655	0.249	2.890	−14.269	0.000	12.271
Net energy imports/energy use	3,672	−0.058	0.777	−2.338	0.225	0.752
Food imports/merchandise imports	3,672	0.078	0.024	0.042	0.079	0.114
Fertilizer imports/agricultural use	3,672	0.909	0.292	0.349	0.893	1.478

TABLE 3 Structural exposure and inflation environment by country.

Country-level structural exposure and inflation environment					
Country	Food imports/merchandise imports	Net energy imports/energy use	Fertilizer imports/agricultural use	Mean annual food inflation (%)	Months above 15% threshold
TUR	0.052	0.752	0.791	16.8	55
KAZ	0.110	−1.215	1.478	9.4	29
BRA	0.053	0.109	0.808	7.5	0
ZAF	0.067	−0.140	0.937	7.0	4
CHL	0.089	0.708	1.250	6.7	21
IDN	0.100	−1.091	0.464	6.6	7
COL	0.114	−2.338	0.871	6.6	19
HUN	0.053	0.566	0.953	6.5	16
IND	0.042	0.313	0.349	6.4	1
MEX	0.063	−0.194	0.689	6.2	0
PHL	0.113	0.433	0.837	4.5	2
PER	0.109	0.044	1.451	4.4	2
POL	0.081	0.294	0.632	4.3	11
ROU	0.086	0.225	0.893	4.0	12
CZE	0.058	0.278	1.076	3.9	11
THA	0.058	0.448	0.949	3.5	0
MYS	0.079	−0.173	1.027	3.5	0

Exposure indicators are time-invariant country averages, as defined in Table 1; negative values for net energy imports indicate net energy exporters. Mean annual food inflation is the country average of the 12-month change in the food consumer price index over 2007:02–2023:12. The final column reports the number of months in which 12-month food inflation exceeded the 15 percent cutoff examined in the monthly state-dependent specification (Section 4.4). Of the 3,451 country-month observations, 190 exceed this cutoff, distributed across 13 economies. Countries are ordered by mean annual food inflation.

where i indexes the country and t indexes the month. α_i denotes country-specific intercepts. β_{ij}, γ_{ij}, δ_{ij}, and θ_{ij} are distributed-lag coefficients associated with exchange rates, Brent crude oil prices, the FAO Food Price Index, and urea prices, respectively. Δ denotes the first-difference operator, ln is the natural logarithm, and ε_{it} is the disturbance term. Standard errors are computed using the Newey-West estimator (Newey and West, 1987) allowing for heteroskedasticity and autocorrelation up to 12 months.

Cumulative pass-through is defined as the sum of the exchange rate coefficients (Equation 2):

$$\mathrm{ERPT}_i = \sum_{j=0}^{12} \hat{\beta}_{ij} \tag{2}$$

The standard error of this sum is obtained via a linear combination test, thereby allowing the statistical significance of the cumulative effect to be directly examined.

The preference for country-specific estimation is motivated by two reasons. First, the Swamy test rejects slope homogeneity; under this condition, a pooled estimator would yield biased results. Second, and more decisively, the rationale relates to identification. The prices of oil, global food, and fertilizers take the same values across all cross-sections, meaning their cross-sectional variance is zero. In pooled or common factor-based estimators, these series are perfectly collinear with time effects or cross-sectional averages and cannot be identified separately. In country-specific time series regressions, however, this identification problem does not arise, and the global series become valid explanatory variables. Because global variables take identical values across all countries in a given month, they are perfectly collinear with a set of unrestricted time fixed effects.

To control for the role of inflation persistence, each country-specific model is re-estimated as an ARDL(p, 12) specification that includes lags of food inflation, with the lag order p selected by the Bayesian information criterion. The long-run multiplier is calculated as the sum of the exchange rate coefficients divided by one minus the sum of the autoregressive coefficients, with standard errors computed using the delta method. Because these are country-level time series regressions with T = 203, dynamic panel bias is of order 1/T and hence negligible.

3.4.3 Cross-country regression of estimated pass-through

The seventeen cumulative coefficients obtained in the first step are then related to observable country characteristics in a cross-sectional regression (Equation 3).

$$\begin{aligned} ERPT_i &= \pi_0 + \pi_1 EnergyDep_i + \pi_2 FoodImp_i \\ &+ \pi_3 FertImp_i + \pi_4 MeanInf_i + \pi_5 SDInf_i + v_i \end{aligned} \tag{3}$$

where $ERPT_i$ is the estimated cumulative exchange-rate pass-through coefficient obtained from the first-stage regressions. $EnergyDep$, $FoodImp$, and $FertImp$ denote the energy import dependence, food import dependence, and fertilizer import dependence, respectively. $MeanInf$ and $SDInf$ denote the country-specific mean and standard deviation of monthly food inflation over the sample period.

$$w_i = \frac{1}{SE\widehat{\left(ERPT_i\right)}^2} \tag{4}$$

where wi denotes the inverse-variance weight assigned to each country-specific pass-through estimate.

The explanatory variables are net energy dependence, food import dependence and fertilizer import dependence, all measured as time-invariant country averages, together with the mean and the standard deviation of monthly food inflation over the sample period. Because the dependent variable is itself estimated and its precision varies across countries, observations are weighted by the inverse of the estimated variance of each coefficient (Equation 4), so that more precisely estimated values receive greater weight. With 17 observations this exercise has limited statistical power and is treated as exploratory rather than explanatory. Its robustness is assessed through leave-one-out estimation and through Spearman rank correlations, which are less sensitive to individual influential observations.

3.4.4 State dependence: quantile regression

To test whether pass-through is dependent on the inflation regime, simultaneous quantile regressions with country fixed effects are estimated:

$$\begin{aligned} Q_\tau(\Delta lnFoodCPI_{it} \mid X_{it} &= \mu_i(\tau) + \sum_{j=0}^{6} \beta_j(\tau)\, \Delta lnExRate_{i,t-j} \\ &+ \sum_{j=0}^{6} \gamma_j(\tau)\, \Delta lnBrent_{i,t-j} + \sum_{j=0}^{6} \delta_j(\tau)\, \Delta lnFAO_{i,t-j} \end{aligned} \tag{5}$$

where $Q\tau(\cdot)$ denotes the conditional quantile function evaluated at quantile τ, X_{it} is the vector of explanatory variables, and $\mu i(\tau)$ represents the country fixed effect at quantile τ. The quantile specification includes three channels. The fertilizer channel enters the country-specific models in Equation 1 but is excluded from the quantile model. A four-channel version is reported as robustness variant R10 in Section 4.6, where cumulative pass-through shifts marginally from 0.120 to 0.125 at the 25th percentile and from 0.277 to 0.258 at the 90th percentile, leaving the overall regime pattern unchanged.

The kurtosis coefficients for the food inflation and exchange rate distributions are 20.3 and 11.1, respectively, both of which substantially exceed the benchmark for a normal distribution. In the presence of such heavy-tailed distributions, estimators based on the conditional mean are inadequate for representing central tendencies and offer no insight into tail behavior. To address this, the estimation is carried out across the quantiles τ ={0.10; 0.25; 0.50; 0.75; 0.90}, with standard errors obtained via bootstrapping. It should be emphasized that these quantiles are defined conditionally: the estimates characterize not the months in which food inflation is high in absolute terms, but rather those in which it is high relative to the level predicted by the explanatory variables. At each quantile, the cumulative pass-through is defined as follows (Equation 6):

$$ERPT(\tau) = \sum_{j=0}^{6} \beta_j(\tau) \tag{6}$$

TABLE 4 Panel diagnostics, unit root and cointegration tests.

Test	Statistic	*p*-value	Average correlation/df
Panel A. Level specification			
Cross-sectional dependence			
Pesaran CD, ln food CPI	163.37	0.000	0.953
Pesaran CD, ln exchange rate	130.56	0.000	0.762
Pesaran CD, fixed-effects residuals	103.97	0.000	0.615
Friedman	2,035.68	0.000	–
Breusch–Pagan LM	12,743.05	0.000	df = 136
Slope homogeneity			
Swamy S	880.80	0.000	df = 16
Panel unit root (CIPS t-bar)			
ln food CPI, intercept	−1.713	0.638	–
ln food CPI, intercept and trend	−1.879	0.992	–
ln exchange rate, intercept	−2.238	0.020	–
ln exchange rate, intercept and trend	−2.469	0.294	–
Cointegration (Westerlund, no trend)			
Gt	−3.026	0.000	–
Ga	−9.397	0.821	–
Pt	−10.729	0.004	–
Pa	−8.233	0.313	–
Panel B. First-difference specification			
Cross-sectional dependence			
Pesaran CD, Δ ln food CPI	24.17	0.000	0.141
Pesaran CD, Δ ln exchange rate	75.72	0.000	0.443
Pesaran CD, model residuals	16.94	0.000	0.140
Friedman	538.47	0.000	–
Breusch–Pagan LM	1,089.70	0.000	df = 136
Slope homogeneity			
Swamy S	88.05	0.000	df = 48
Panel unit root (CIPS t-bar)			
Δ ln food CPI	−5.872	0.000	–
Δ ln exchange rate	−6.036	0.000	–

N = 17 countries, T = 216 months (2006:01–2023:12). Panel A reports diagnostics computed on the level series and on the residuals of a fixed-effects regression of ln food CPI on ln exchange rate. Panel B reports the corresponding diagnostics for the first-difference specification used in the estimation, where the residuals are obtained from a fixed-effects regression of monthly food inflation on the contemporaneous and six lagged values of currency depreciation, oil price growth, global food price growth, and urea price growth, representing the full empirical specification. The average correlation column reports the mean pairwise correlation for series-level CD tests and the mean absolute off-diagonal residual correlation for residual-based tests. Swamy S is computed directly as the weighted deviation of country-specific slope vectors from the pooled fixed-effects estimator, since the Pesaran–Yamagata test is unavailable in the software version used; the number of slope parameters is one in Panel A and three in Panel B. Swamy's test over-rejects under cross-sectional dependence and should therefore be read jointly with the CD results. CIPS tests are augmented by four lags. Westerlund tests are reported for the specification without a deterministic trend, with two lags and one lead; when a linear trend is included, the rejection disappears (Section 4.1). The global series (oil, urea, the FAO index) are identical across countries and therefore have no cross-sectional variance; they are tested individually with augmented Dickey–Fuller regressions and are non-stationary in levels and stationary in first differences in every case.

The hypothesis of state dependence is tested by evaluating the equality of cumulative pass-through coefficients across different quantiles (Equation 7):

$$H_0 : ERPT_{(\tau 1)} = ERPT_{(\tau 2)}$$
$$H_1 : ERPT_{(\tau 1)} \neq ERPT_{(\tau 2)} \quad (7)$$

This restriction is tested using a Wald test; the results are presented separately for the quantile pairs (0.10; 0.90), (0.25; 0.90), and (0.50; 0.90). The same procedure is applied to the global food and oil channels to determine whether the regime dependence is channel-specific.

Fixed effects are incorporated directly into the model as country dummies. Given the length of the time dimension (209 observations per country), the incidental parameters problem arising from the estimation of fixed effects in quantile regression is expected to remain limited. Statistical inference explicitly accounts for the panel structure of the data. Analytical standard errors clustered by country are reported alongside the observation-level bootstrap of the baseline specification, as the Parente and Santos Silva (2016) test rejects the null hypothesis of no intra-cluster

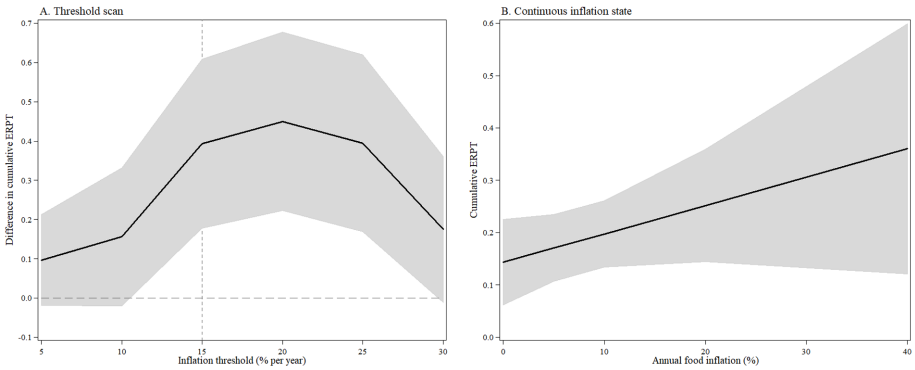


FIGURE 2
State dependence in exchange rate pass-through. Panel **(A)** shows the difference in cumulative pass-through between high- and low-inflation regimes across alternative thresholds for the observed twelve-month food inflation rate, along with 95 percent confidence intervals; the dashed vertical line indicates the 15 percent threshold adopted in the baseline specification. Panel **(B)** displays the cumulative pass-through as a function of the continuous inflation state. Both panels use country fixed effects and Driscoll-Kraay standard errors.

correlation across all quantiles. Tests of inter-quantile equality require the joint covariance matrix of the coefficients and therefore rely on a cluster bootstrap with 499 replications that resamples entire country time series, preserving within-country serial correlation. Because the panel contains 17 clusters, p-values are evaluated against an $F(1, 16)$ distribution rather than an asymptotic chi-squared distribution.

3.4.5 State dependence: threshold approach

Conditional quantiles identify observations where food inflation is high relative to what covariates predict, which is conceptually distinct from periods of objectively high inflation. To provide a test of state dependence consistent with the Taylor hypothesis, the exchange rate terms are interacted with an indicator for the observed inflation environment (Equation 8):

$$\begin{aligned}\Delta ln\, FoodCPI(i,t) &= \alpha(i) + \Sigma\, \beta(j)\, \Delta ln\, ExRate(i,t-j) \\ &+ \Sigma\, \theta(j)\left[\, \Delta ln\, ExRate(i,t-j) \times High(i,t-1)\, \right] \\ &+ \Gamma' Z(i,t) + \varphi\, High(i,t-1) + \varepsilon(i,t) \end{aligned} \quad (8)$$

where High $(i,t-1)$ equals one if 12-month food inflation in country i at time $t-1$ exceeds a given threshold, and Z includes terms for oil, fertilizer, and global food prices. Because the state indicator is lagged, it is not a function of contemporaneous shocks.

The cumulative difference $\Sigma\, \theta(j)$ is the primary object of interest and provides the study's principal test of state dependence. Standard errors are computed using the Driscoll-Kraay method, which is robust to serial correlation and the residual cross-sectional dependence documented in Table 4. The threshold is set at 15 percent annual food inflation in the baseline specification, a conventional cutoff for high inflation in emerging economies, with results across the 5 to 30 percent range reported in reported in Figure 2 and Supplementary Table S7. A continuous version, in which the exchange rate terms are interacted with the demeaned inflation state, is also estimated to check against the potential arbitrariness of any binary cutoff.

3.4.6 Direction of predictive association

To evaluate the potential bidirectional relationship between the exchange rate and inflation, the Dumitrescu-Hurlin panel causality test (Dumitrescu and Hurlin, 2012) is applied. The test is based on the average of country-specific Wald statistics in heterogeneous panels and can be employed with bootstrapped critical values under cross-sectional dependence. It is applied to the first differences with two lags and shown for both directions. It should be noted that the alternative hypothesis indicates causality in at least one panel unit rather than across all units.

3.4.7 Long-run check

To complement the main findings, the common correlated effects mean group estimator (Pesaran, 2006) is applied to the level specification. By including cross-sectional averages as explanatory variables in the model, this estimator accounts for unobserved common factors and accommodates slope heterogeneity. The results are presented as supporting evidence for the existence of a long-run relationship; however, the primary claims of the study are not based on this estimation.

3.5 Robustness strategy

The robustness of the main findings is tested using 10 alternative specifications. These include introducing dummy variables for crisis periods, splitting the sample in 2015, using end-of-period exchange rates instead of period averages, individually excluding outlier countries (Turkiye and Colombia), incorporating the geopolitical risk index modifying the lag structure, and augmenting the quantile specification with the fertilizer channel.

4 Results

4.1 Preliminary tests

Three panel characteristics determining the selection of the appropriate estimator have been identified. The test results are presented in Table 4.

Cross-sectional dependence is pervasive in the level series. The Pesaran CD statistic is 163.37 for food consumer prices and 130.56 for the nominal exchange rate, with average pairwise correlations of 0.95 and 0.76 respectively, and independence is rejected at any conventional level. The same conclusion holds for the residuals of a level specification, where the CD statistic is 103.97 and the average absolute off-diagonal residual correlation is 0.615. Friedman and

TABLE 5 Country-specific cumulative exchange rate pass-through: distributed lag and ARDL estimates.

Country	Cumulative ERPT (DL)	SE	95% CI	R2	Long-run ERPT (ARDL)	SE	AR order (*p*)
TUR	0.807***	(0.128)	[0.556; 1.059]	0.449	0.809***	(0.138)	1
HUN	0.505**	(0.238)	[0.038; 0.972]	0.328	0.584**	(0.295)	1
CHL	0.338***	(0.116)	[0.111; 0.566]	0.205	0.327**	(0.140)	1
COL	0.336***	(0.124)	[0.094; 0.579]	0.327	0.373**	(0.143)	1
ZAF	0.250***	(0.052)	[0.148; 0.352]	0.297	0.272***	(0.059)	2
IND	0.237	(0.158)	[−0.073; 0.548]	0.184	0.212	(0.167)	2
POL	0.212*	(0.118)	[−0.020; 0.444]	0.170	0.283**	(0.135)	1
ROU	0.178	(0.149)	[−0.115; 0.471]	0.247	0.200	(0.163)	1
CZE	0.178	(0.143)	[−0.102; 0.458]	0.167	0.200	(0.152)	1
BRA	0.142***	(0.051)	[0.042; 0.242]	0.318	0.142**	(0.055)	2
MYS	0.130**	(0.050)	[0.032; 0.228]	0.175	0.142**	(0.056)	1
PER	0.091	(0.134)	[−0.171; 0.353]	0.208	0.099	(0.135)	1
THA	0.075	(0.122)	[−0.163; 0.313]	0.155	0.056	(0.126)	1
KAZ	0.065	(0.066)	[−0.064; 0.194]	0.358	0.088	(0.091)	2
MEX	0.060	(0.078)	[−0.092; 0.212]	0.213	0.086	(0.086)	1
PHL	0.024	(0.177)	[−0.323; 0.372]	0.186	−0.005	(0.235)	1
IDN	−0.012	(0.150)	[−0.306; 0.281]	0.122	0.015	(0.134)	2

***$p < 0.01$, **$p < 0.05$, *$p < 0.10$. The dependent variable is monthly food inflation. Columns 2 through 5 report the distributed lag specification with 12 lags of currency depreciation and six lags of oil, global food, and urea prices, with standard errors computed using the Newey-West method with 12 lags. Columns 6 through 8 report ARDL(p, 12) specifications that include lags of food inflation, where p is selected by the Bayesian information criterion. The long-run multiplier is calculated as the sum of the exchange rate coefficients divided by one minus the sum of the autoregressive coefficients, with standard errors obtained via the delta method. Because the sum of the autoregressive coefficients ranges between 0.08 and 0.54 (Supplementary Table S8), the long-run multiplier is well defined in all cases. The Spearman rank correlation between the two sets of estimates is 0.978 (Pearson 0.990), and the mean increases from 0.213 to 0.228, indicating that the pass-through estimates are not driven by omitted food inflation dynamics. Since these are country-level time series regressions with $T = 203$, dynamic panel bias is of order 1/T and negligible.

Breusch–Pagan LM statistics point in the same direction. This pattern is unsurprising given the shared exposure of these economies to world commodity markets and to the global financial cycle.

Dependence weakens markedly once the model is estimated in first differences. The CD statistic falls to 24.17 for food inflation and to 16.94 for the residuals of the estimated specification, and the average absolute residual correlation declines from 0.615 to 0.140. This decline indicates that including global oil and food price series captures a substantial part of the common factor structure. Dependence is nonetheless not eliminated, which has implications for inference that are discussed in Section 5.

Slope homogeneity is rejected in both specifications. Because the Pesaran–Yamagata test is unavailable in the software version used, Swamy's S statistic is computed directly as the weighted deviation of country-specific slope vectors from the pooled fixed-effects estimator. The statistic is 880.80 with 16 degrees of freedom in the level specification and 88.05 with 48 degrees of freedom in the first-difference specification, rejecting common slopes at the 1% level in both cases. Two qualifications apply. Swamy's test over-rejects in the presence of cross-sectional dependence, so the two sets of results in Table 4 should be read together rather than as independent evidence. More importantly, the case for country-specific estimation does not rest on this test alone: the global price series take identical values across countries in each month and are therefore perfectly collinear with unrestricted time effects, so their coefficients cannot be separately identified in specifications that absorb month effects, whereas they are valid regressors in country-level time series regressions.

Regarding the order of integration, the Pesaran CIPS test fails to reject the unit root hypothesis for food consumer prices in both specifications (t −bar −1.71 in the model with an intercept; −1.88 in the model with an intercept and trend). In contrast, the first differences are strongly stationary (t-bar −5.87, $p < 0.001$). The exchange rate exhibits similar behavior when a trend is added (t-bar −2.47, $p = 0.294$ in levels; −6.04, $p < 0.001$ in differences). Since global series take identical values for all countries, their cross-sectional variances are zero. Tested individually using Augmented Dickey–Fuller regressions, oil prices, urea prices, the FAO index, and the supply chain pressure index (Benigno et al., 2022) are each non-stationary in levels but stationary in first differences.

The findings regarding cointegration are mixed and are presented as such. In the specification without a deterministic trend, two of the four Westerlund statistics reject the null hypothesis of no cointegration ($G_t = -3.03$, $p < 0.001$; $P_t = -10.73$, $p = 0.004$); conversely, the group mean statistics fail to reject it ($G_a = -9.40$, $p = 0.821$; $P_a = -8.23$, $p = 0.313$). When a linear trend is included, the rejection disappears entirely. Given that group mean variants are known to possess low power in heterogeneous panels, and imposing a deterministic trend on two series that inherently carry stochastic trends is economically difficult to justify, the trendless specification is adopted. Estimating in first differences circumvents the order of integration issues, thereby eliminating the concern of spurious regression.

4.2 Country-specific pass-through

The cumulative pass-through coefficients obtained from country-specific distributed lag regressions are presented in Table 5 and Figure 3. In the model, monthly food inflation is estimated using 12 lags of exchange rate depreciation, while six lags each of global oil,

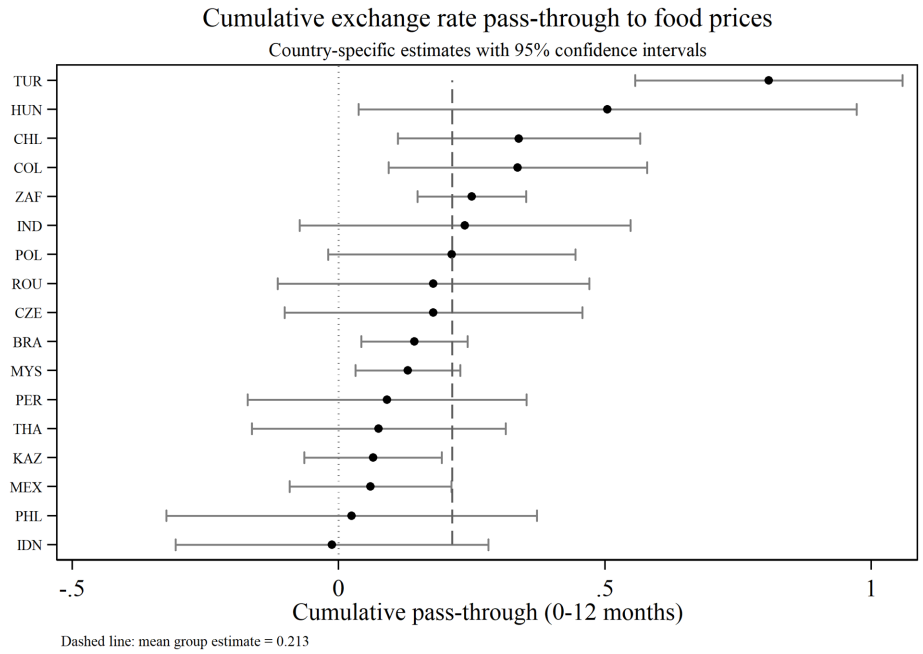


FIGURE 3
Country-specific cumulative exchange rate pass-through estimates with 95% confidence intervals. The dashed vertical line represents the mean-group estimate of 0.213.

food, and fertilizer prices are included as control variables. Standard errors are calculated using the Newey–West method, which allows for serial correlation up to 12 months.

The mean group estimate is 0.213: a 10% depreciation over a 12-month period increases the food consumer price index by approximately 2.1% on average. This value falls within the range shown for overall consumer prices in emerging markets, indicating that, on average, food prices are not significantly more sensitive to the exchange rate than the broader consumer basket.

The mean conceals substantial heterogeneity. Estimation precision varies significantly across countries, largely reflecting the level of domestic exchange rate volatility. The estimates range from −0.012 for Indonesia to 0.807 for Turkiye, spanning a range of more than 0.8; only seven of the 17 coefficients are individually significant at the 5% level. Turkiye is a clear outlier, with a pass-through approximately four times the group mean; it is followed by Hungary at 0.505, and then by Chile and Colombia at approximately 0.34. At the other end of the distribution, Indonesia, the Philippines, Mexico, Kazakhstan, and Thailand all exhibit cumulative coefficients that are statistically indistinguishable from zero and remain below 0.10. This distribution implies that studies presenting a single pooled pass-through elasticity for emerging markets describe a central tendency applicable to very few of their covered economies.

4.3 Structural exposure heterogeneity

The next step is to investigate the drivers of this distribution. The 17 country-specific estimates are modeled based on observable structural characteristics and weighted by the inverse of their estimation variances, ensuring that more precisely estimated coefficients receive greater weight. Food import dependency enters the model with a negative and insignificant coefficient (unweighted: −2.84, p = 0.139; weighted: −0.76, p = 0.628). Net energy dependency is insignificant across all specifications; the same applies to fertilizer import dependency. The average food inflation level initially appears to perform better: the coefficient is 0.030 (p = 0.115), with a raw correlation of 0.71. However, this relationship does not withstand closer scrutiny. When Turkiye is excluded, the coefficient drops to 0.001, and the t-statistic falls to 0.12; the Spearman rank correlation declines from 0.28 to 0.13. A jackknife procedure confirms that this result is driven entirely by Turkiye; the exclusion of any of the other 16 countries leaves the coefficient at approximately 0.030. The same holds true for inflation volatility. The underlying scatter plot is presented in Supplementary Figure S1. Therefore, the power of a cross-sectional design with 17 observations to explain cross-country differences in pass-through using structural indicators is limited; consequently, this stage is treated as descriptive rather than explanatory. The primary takeaway is that the search for an explanation must shift from cross-country differences to within-country variations. The pattern is visible in Table 3 without recourse to regression. Turkiye combines the second lowest food import dependence in the sample with the highest cumulative pass-through, while Kazakhstan is a net energy exporter with the highest fertilizer import dependence and a cumulative pass-through of 0.065. What separates the two is not structural exposure but the inflation environment.

4.4 Pass-through and the inflation environment

Whether pass-through varies with the inflation environment can be framed in two ways, and this paper addresses both. The first approach defines the inflation state directly by using the actual food inflation rate experienced by each country. The second characterizes the conditional distribution of food inflation using quantile regression. The two approaches are complementary. The first corresponds

TABLE 6 State dependence in exchange rate pass-through.

Panel A. Explicit state-dependent specifications using observed food inflation				
Statistic	(1) Country median	(2) 10% threshold	(3) 15% threshold	(4) Continuous
Cumulative ERPT, low-inflation state	0.178*** (0.037)	0.179*** (0.038)	0.147*** (0.029)	
Cumulative ERPT, high-inflation state	0.268*** (0.072)	0.335*** (0.095)	0.541*** (0.112)	
Difference	0.090 (0.068)	0.156* (0.091)	0.393*** (0.110)	0.005 (0.004)
p-value of difference	0.182	0.085	<0.001	0.138
Bonferroni-adjusted *p*-value	–	–	0.0027	–
Observations in high-inflation state	1,726	632	190	–
Observations	3,451	3,451	3,451	3,451

Panel B. Mean-group within-country estimates at the 15 percent threshold				
Economy	Difference	SE	*t*	High-state months
Turkiye	0.471	(0.233)	2.02	55
Poland	0.455	(0.158)	2.88	11
Hungary	0.424	(0.172)	2.47	16
Romania	0.405	(0.254)	1.60	12
Kazakhstan	0.403	(0.289)	1.39	29
Colombia	0.290	(0.145)	1.99	19
Chile	0.140	(0.164)	0.86	21
Czechia	0.124	(0.284)	0.44	11
Mean group	0.339***	(0.049)	6.90	174
Mean group, excluding Turkiye	0.320***	(0.052)	6.12	119
Mean group, inverse-variance weighted	0.336	–	–	174
Pooled estimate, for comparison	0.393***	(0.110)	3.57	190

Panel C. Formal threshold estimation		
Statistic	Overlapping windows	Non-overlapping
Estimated threshold (% per year)	7.56	6.83
95% confidence interval	–	[5.96; 6.86]
Bootstrap F statistic	126.40	17.31
Bootstrap p-value	<0.001	<0.001
Cumulative ERPT, below threshold	0.070*** (0.011)	0.059** (0.029)
Cumulative ERPT, above threshold	0.232*** (0.011)	0.210*** (0.027)
Trimming parameter	15%	15%
Bootstrap replications	500	300
Observations	3,451	578

Panel A: The regime indicator is the 12-month food inflation rate observed in the preceding month, so the state is not a function of the model's own residuals. Columns (1) to (3) interact all seven exchange rate terms with a binary high-inflation indicator; column (4) interacts them with the demeaned continuous inflation state, so the reported difference represents the change in cumulative pass-through per percentage point of annual inflation. The Bonferroni-adjusted p-value corrects for the six thresholds examined in the sensitivity analysis reported in Figure 2. All specifications include country fixed effects and use Driscoll–Kraay standard errors with six lags, which are robust to serial correlation and the residual cross-sectional dependence documented in Table 4. The estimation sample contains 3,451 rather than 3,553 observations because construction of the 12-month inflation state requires 13 initial observations per country.
Panel B: The specification in column (3) of Panel A is estimated separately for each economy, and the country-specific differences are averaged so that the comparison rests entirely on within-country variation. Newey–West standard errors with six lags are used in the country regressions. The mean-group standard error is calculated as the standard deviation of the country estimates divided by the square root of the number of economies. The exercise is restricted to economies with at least 10 months in the high-inflation state. Since the specification contains seven interaction terms, estimates for economies with fewer high-state observations are highly unstable, as illustrated in Supplementary Table S5. Of the 190 high-state observations, 55 are from Turkiye, with the remainder distributed across 12 other economies.
Panel C: Hansen (1999) panel threshold estimation applied to six-month cumulative changes, with the lagged twelve-month food inflation rate as the threshold variable and the six-month cumulative depreciation as the regime-dependent regressor. The overlapping specification uses all monthly observations; the non-overlapping specification retains June and December observations only, so that the six-month windows do not overlap. Bootstrap p-values test the null of no threshold. ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$ throughout the table.

more closely to the mechanism described by Taylor (2000), while the second makes use of the full sample rather than relying only on the smaller number of observations associated with high-inflation periods.

Panel A of Table 6 reports the first approach. The regime indicator is the twelve-month food inflation rate observed in the preceding month, so it reflects the environment in which importers, food processors and retailers were setting prices rather than any feature of the model's residuals. When the regime is defined relative to each country's own median, cumulative pass-through is 0.178 in the low state and 0.268 in the high state; the difference points in the direction the Taylor mechanism predicts but is not statistically distinguishable from zero ($p = 0.182$). At the 10 percent threshold, cumulative pass-through increases from 0.179 in the low-inflation state to 0.335 in the high-inflation state, corresponding to a difference of 0.156 ($p = 0.085$). This indicates that the relationship is not linear in the inflation rate. Price-setters along the food supply chain do not adjust their behavior gradually as inflation edges up, but change it once inflation reaches a level they treat as persistent.

These results suggest that the relationship between exchange rate pass-through and the inflation environment may be nonlinear. Pass-through changes relatively little at moderate inflation rates but becomes stronger as inflation moves into higher ranges, which is broadly consistent with the mechanism proposed by Taylor (2000).

Figure 2 examines this relationship across a range of potential threshold values. The difference in cumulative pass-through remains relatively small and imprecisely estimated at moderate inflation rates but increases as the threshold approaches 15 percent and remains elevated at higher levels. At the 15 percent threshold, cumulative pass-through is 0.147 below the threshold and 0.541 above it, corresponding to a difference of 0.393 ($t = 3.573$). Since six threshold values are considered, a Bonferroni correction is applied to account for multiple testing. The adjusted p-value is 0.0027, and the difference remains statistically significant at the 1 percent level. Panel B of Figure 2 presents the relationship in continuous form. Cumulative pass-through is estimated at 0.143 when annual food inflation is zero, 0.198 at 10 percent, 0.252 at 20 percent, and 0.360 at 40 percent.

The economic significance of this difference is also notable. When annual food inflation is below 15 percent, a 10 percent currency depreciation is associated with an increase of approximately 1.5 percent in consumer food prices over six months. When annual food inflation exceeds 15 percent, the corresponding increase is approximately 5.4 percent. These estimates suggest that the implications of exchange rate movements for consumer food prices may become more pronounced during periods of elevated inflation.

One possible concern is that the results may partly reflect differences in country composition. Slope homogeneity is rejected, and high-inflation observations are more common in economies with relatively high average pass-through. Under these conditions, a pooled specification with country fixed effects may not fully distinguish state dependence from cross-country differences in slopes. Panel B of Table 6 therefore estimates the difference between inflation states separately for each economy with at least ten observations in the high-inflation state and then averages the country-specific estimates. This approach bases the comparison entirely on within-country variation. The resulting mean-group difference is 0.339 (t = 6.90), compared with 0.393 in the pooled specification. The estimated difference is positive in all eight economies included in this exercise. The country-level results provide further support for this interpretation. Kazakhstan, Romania, and Poland have relatively modest cumulative pass-through estimates in Table 5, at 0.065, 0.178, and 0.212, respectively, but their estimated differences between the high- and low-inflation states are 0.403, 0.405, and 0.455. The results also remain similar when Turkiye is excluded. Although Turkiye accounts for 55 of the 190 high-inflation observations, excluding it leaves the mean-group difference at 0.320 (t = 6.12). The restriction to eight economies reflects the data requirements of the specification rather than a discretionary sample choice. Economies with only a small number of observations in the high-inflation state do not provide sufficient variation for reliable estimation of the interaction terms.

A second issue concerns the choice of the inflation threshold. Panel C reports formal threshold estimates following Hansen (1999), using a 15 percent trimming parameter to ensure sufficient observations in each regime. Based on six-month cumulative changes, the estimated threshold is 7.56 percent annual food inflation, with a bootstrap p-value below 0.001 based on 500 replications. Cumulative pass-through increases from 0.070 below the estimated threshold to 0.232 above it. Since the six-month dependent variable is constructed from overlapping windows, the analysis is also repeated using non-overlapping semi-annual observations. This specification produces a threshold estimate of 6.83 percent, with a confidence interval of [5.96; 6.86] ($F = 17.31$, bootstrap $p < 0.001$, 300 replications).

The formal threshold estimates are therefore lower than the 15 percent level at which the difference becomes statistically detectable in the monthly specification. At a threshold of 7.56 percent, the monthly difference is 0.106 and is not statistically significant ($p = 0.176$). These results need not be interpreted as contradictory. The formal threshold estimates suggest that the relationship begins to change at relatively moderate inflation rates, while the monthly estimates indicate that the difference becomes sufficiently large to be statistically distinguishable only at higher inflation levels. The main result is therefore less dependent on a particular cutoff value and relates more broadly to the nonlinear relationship between the inflation environment and exchange rate pass-through, with relatively limited variation at moderate inflation rates and a stronger response as inflation reaches higher levels.

Table 7 presents the second approach. Simultaneous quantile regressions with country fixed effects are estimated across the conditional distribution of food inflation. Cumulative exchange rate pass-through increases from 0.120 at the twenty-fifth percentile to 0.277 at the ninetieth percentile. Since these quantiles are conditional, they capture periods in which food inflation is high relative to the level predicted by the covariates rather than periods of high inflation in absolute terms. The results are therefore interpreted as evidence of distributional heterogeneity consistent with the Taylor mechanism rather than as a test of it in terms of observed inflation.

Country composition may also influence the quantile estimates. When country-specific exchange rate slopes are allowed (Supplementary Table S4), mean-group cumulative pass-through increases from 0.140 at the twenty-fifth percentile to 0.248 at the ninetieth percentile, corresponding to an increase of 78 percent compared with 131 percent in the pooled specification. This suggests that part of the pooled difference reflects country

TABLE 7 Cumulative pass-through across the food inflation distribution.

Variable	$\tau = 0.10$	$\tau = 0.25$	$\tau = 0.50$	$\tau = 0.75$	$\tau = 0.90$
Exchange rate depreciation	0.130***	0.120***	0.147***	0.185***	0.277***
Bootstrap SE (observation-level)	(0.020)	(0.019)	(0.017)	(0.021)	(0.031)
Cluster-robust SE	(0.031)	(0.034)	(0.032)	(0.033)	(0.045)
Global food price growth	0.107***	0.111***	0.141***	0.166***	0.186***
Bootstrap SE (observation-level)	(0.018)	(0.018)	(0.012)	(0.016)	(0.026)
Cluster-robust SE	(0.026)	(0.031)	(0.021)	(0.024)	(0.025)
Oil price growth	−0.010	−0.016	−0.019**	−0.016**	−0.000
Bootstrap SE (observation-level)	(0.007)	(0.007)	(0.005)	(0.007)	(0.013)
Cluster-robust SE	(0.010)	(0.011)	(0.008)	(0.008)	(0.010)
Equality of cumulative effects, *F*					
Exchange rate	13.16***	15.68***	16.38***	–	ref.
Global food prices	5.07**	6.88**	4.21*	–	ref.
Oil price	0.43	1.20	3.15*	–	ref.
Country fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	3,553	3,553	3,553	3,553	3,553

The dependent variable is monthly food inflation, measured as the first difference of the log food consumer price index. Estimates are obtained from simultaneous quantile regressions with country fixed effects, evaluated across the conditional distribution. Each entry reports the cumulative effect over the contemporaneous month and six lags. Two sets of standard errors are reported: the first is based on an observation-level bootstrap, while the second is analytical and clustered by country. The Parente and Santos Silva (2016) test rejects the null hypothesis of no intra-cluster correlation at each quantile ($\tau = 0.25$: $T = -2.69$, $p = 0.007$; $\tau = 0.90$: $T = -2.61$, $p = 0.009$), indicating that clustered standard errors are the appropriate basis for inference. Tests of equality compare the cumulative effect at the specified quantile with that at the 90th percentile using a cluster bootstrap with 499 replications resampling entire country time series, with p-values computed against F(1, 16) reflecting 17 clusters. Percentile confidence intervals are reported in Supplementary Table S2, and the full lag distribution is reported in Supplementary Table S1. Because quantiles are conditional, the estimates identify months with high food inflation relative to expectations rather than simply high-inflation months.
***$p < 0.01$, **$p < 0.05$, *$p < 0.10$.

composition, although the direction and statistical significance of the relationship remain unchanged. The threshold estimates are less sensitive to this issue, providing additional support for treating the threshold specification as the primary approach. Inference requires particular attention because the residuals exhibit both serial correlation and cross-sectional dependence, while the available resampling procedures do not preserve both simultaneously. Two procedures are therefore considered. The country-cluster bootstrap resamples complete country time series and preserves within-country serial correlation, while the time-block bootstrap resamples twelve-month blocks of the full cross-section and preserves contemporaneous cross-country dependence (Supplementary Table S3). The exchange rate results remain statistically significant under both procedures. For the comparison between the twenty-fifth and ninetieth percentiles, the equality test yields $F = 15.68$ ($p = 0.001$) under country clustering and $F = 14.62$ ($p = 0.001$) under time blocking.

The evidence for the global food price channel is less robust. Under country clustering, its cumulative effect increases from 0.107 at the tenth percentile to 0.186 at the ninetieth percentile, with equality rejected at the 5 percent level ($F = 5.07$, $p = 0.039$). Under time blocking, however, the corresponding test yields $F = 2.01$ ($p = 0.175$). Similar differences between the two resampling procedures are observed at the twenty-fifth percentile and the median. The difference is also reflected in the standard errors. At the ninetieth percentile, the standard error of the global food price coefficient increases from 0.028 to 0.070 when cross-country dependence is preserved. Since global food prices take the same value across countries within a given month, inference that accounts for cross-country dependence is particularly relevant for this variable. Together with the absence of a significant difference when the regime is defined using observed inflation (0.017, $p = 0.688$), these results provide limited evidence of regime dependence in the global food price channel.

The results for the oil price channel provide little evidence of regime dependence under either resampling procedure. The comparison between the tenth and ninetieth percentiles is statistically insignificant under both country clustering ($F = 0.43$) and time blocking ($F = 0.32$), with similar results at the twenty-fifth percentile. The median comparison is marginally significant under country clustering ($F = 3.15$, $p = 0.095$) but not under time blocking ($F = 0.87$). Moreover, the conditional oil price coefficient does not become stronger at the upper quantile. Taken together, the results do not provide consistent evidence that oil price pass-through increases with the inflation environment.

4.5 The exchange rate and the energy channel

In the main specification, the oil price coefficient is estimated conditional on the global food price index and fertilizer prices. Since part of the effect of energy prices on domestic food prices may operate

TABLE 8 Decomposition of the oil price effect across nested specifications.

Variable	(1) Oil only	(2) +Urea	(3) +FAO	(4) Full model
Cumulative oil price effect	0.008 (0.012)	0.000 (0.012)	−0.028** (0.012)	−0.012 (0.011)
Cumulative urea price effect		0.019 (0.013)	0.017 (0.013)	0.001 (0.012)
Cumulative global food price effect			0.108*** (0.027)	0.177*** (0.031)
Cumulative exchange rate effect				0.239*** (0.058)
Model F	0.85	0.98	2.40***	6.88***
Within R^2	0.004	0.015	0.033	0.098
Observations	3,553	3,553	3,553	3,553

Regressions include country fixed effects and Driscoll-Kraay standard errors with six lags. All columns use the same estimation sample. Each entry represents the sum of the contemporaneous coefficient and six lags. Column (1) reports the total oil effect independent of other channels, while Column (4) reports the remaining direct effect after conditioning on the fertilizer, global commodity, and exchange rate channels. The total oil effect is indistinguishable from zero ($p = 0.476$) and the entire specification is statistically insignificant ($p = 0.546$), with a 95 percent confidence interval of [−0.014, 0.031]. The equality of cumulative exchange rate and oil effects in Column (4) is strongly rejected ($F = 22.91$, $p < 0.001$). ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$.

TABLE 9 Robustness of regime dependence (R0–R10).

Specification	Countries	Obs.	$\tau = 0.25$	$\tau = 0.50$	$\tau = 0.90$	Increase (%)	p
R0 Baseline	17	3,553	0.120	0.147	0.277	131.5	<0.001
R1 Crisis dummies	17	3,553	0.131	0.152	0.258	96.3	<0.001
R2 Subperiod 2006–2014	17	1,717	0.122	0.148	0.175	43.8	0.233
R3 Subperiod 2015–2023	17	1,836	0.125	0.143	0.302	141.5	<0.001
R4 End-of-period exchange rate	17	3,553	0.118	0.136	0.231	96.7	<0.001
R5 Excluding Turkiye	16	3,344	0.107	0.123	0.228	112.9	<0.001
R6 Excluding Colombia	16	3,344	0.109	0.138	0.270	147.1	<0.001
R7 With geopolitical risk index	14	2,926	0.135	0.157	0.247	83.8	0.005
R8 Short lags (0–3)	17	3,604	0.083	0.092	0.168	102.5	0.006
R9 Long lags (0–9)	17	3,502	0.139	0.160	0.312	125.0	<0.001
R10 Four-channel (incl. urea)	17	3,553	0.125	0.147	0.258	107.2	<0.001

Each row reports the cumulative exchange rate pass-through for three quantiles of the conditional food inflation distribution, calculated as the sum of the contemporaneous coefficient and six lags. The Increase column reports the percentage change between the 25th and 90th percentiles, and the final column reports the p-value for the null hypothesis of equality between the two, obtained from a Wald test following simultaneous quantile regression with 200 bootstrap replications. Regime dependence is rejected at the 1 percent level in nine of the ten alternative specifications (R1–R10), with the exception of the first subperiod (R2), where an increase is present but not statistically significant. Specifications R0 through R9 use the three-channel specification of Equation 5, whereas R10 adds the fertilizer channel. The robustness variants use 200 bootstrap replications so that specifications remain comparable across rows; the baseline is additionally reported with cluster-robust inference and a 499-replication cluster bootstrap in Table 7. Spot checks confirm that the change in procedure affects precision rather than the estimates: at the ninetieth percentile, cluster-robust standard errors give 0.302 ($t = 5.63$) for R3 and 0.228 ($t = 6.68$) for R5, against point estimates identical to those reported here.

through global commodity markets, this coefficient captures the direct effect conditional on these channels rather than the overall effect of energy prices. Table 8 examines this distinction by separating the direct and indirect components of the energy price effect.

Table 9 reports a sequence of nested specifications estimated using the same sample. Column (1) estimates the oil price effect using country fixed effects and the contemporaneous value and six lags of oil price growth, without additional controls. Over the six-month horizon, the cumulative effect is 0.008 and is not statistically significant ($p = 0.476$). The specification as a whole is also insignificant and explains approximately 0.4 percent of the within-country variation in food inflation. Adding fertilizer prices in column (2) leaves the oil price effect close to zero, while the cumulative effect of urea prices is also statistically insignificant (0.019, $p = 0.157$). The negative oil coefficient observed in columns (3) and (4) appears only after the global food price index is introduced. This suggests that the negative coefficient is related to conditioning on the global food price channel rather than indicating a negative cost effect of oil prices. The six-month horizon may, however, be too short to capture the full transmission process. The estimated effect changes. The cumulative effect of oil prices reaches 0.045 over twelve months ($p = 0.012$) and 0.064 over eighteen months ($p = 0.026$). The estimated effect is therefore relatively small but becomes statistically detectable at longer horizons, suggesting that transmission through production and distribution costs may take time. The absence of a statistically significant effect is thus limited to shorter horizons.

Two qualifications are important. First, an unconditional oil price coefficient may reflect both supply and demand disturbances, which can have different implications for food prices. These effects cannot be separately identified within the present framework. As a partial check, the specification is re-estimated controlling for global supply chain pressure, which captures part of the common variation associated with

global demand conditions. The cumulative oil price effect remains similar at 0.009 over six months and 0.046 over twelve months, suggesting that the estimated long-horizon effect is not primarily driven by omitted global demand conditions. Second, Brent and urea are global benchmarks and do not directly capture domestic fuel, electricity, fertilizer, or transport costs, which may affect food prices with different timing across countries. The estimates should therefore be interpreted as evidence on the global energy price channel rather than on the overall energy costs faced by domestic food supply chains.

The relative magnitude of the estimated effects provides an additional perspective. At policy-relevant horizons, a 10 percent increase in crude oil prices is associated with an increase of approximately 0.5 percent in consumer food prices, compared with about 2.4 percent following a depreciation of the same magnitude. The hypothesis that the cumulative exchange rate and oil price effects are equal is rejected in the full model ($F = 22.91$, $p < 0.001$), as well as at the median ($F = 22.15$) and the ninetieth percentile ($F = 27.85$) of the conditional distribution; see also Supplementary Table S6.

These results relate specifically to consumer food prices and can be considered alongside the broader literature documenting links between oil and commodity prices. Retail food prices reflect several components beyond primary agricultural commodities, including processing, packaging, distribution, rent, and labour costs. In the United States, for example, the farm share of the consumer food dollar was 11.8 cents in 2024, with energy representing one of twelve supply-chain industry groups (USDA ERS, 2026). The commodity component therefore represents only part of the final retail price, which may partly explain why relationships observed at the commodity level become weaker at the consumer level. For the emerging market economies considered in this study, the results suggest that exchange rate movements are more closely associated with consumer food price changes than global oil price movements.

The direction of the relationship provides further evidence consistent with this interpretation. The Dumitrescu–Hurlin test, applied to first differences with two lags, rejects the null hypothesis that depreciation does not Granger-predict food inflation (Z-tilde = 3.21, $p = 0.001$), while the reverse hypothesis cannot be rejected (Z-tilde = 0.54, $p = 0.589$). The alternative hypothesis indicates predictive precedence in at least one panel unit and should not be interpreted as applying uniformly across all economies. These results describe the direction of predictive association rather than establishing structural exogeneity. Common shocks affecting both exchange rates and food prices, including monetary policy changes, global risk conditions, capital flows, and supply disruptions, cannot be ruled out by this test. As an additional assessment of the longer-run relationship, the common correlated effects mean group estimator applied to the level specification produces an exchange rate coefficient of 0.189 ($p = 0.043$), which is broadly comparable in magnitude to the mean of the country-specific cumulative estimates.

4.6 Robustness

Table 9 presents ten alternative specifications. The finding of regime dependence remains valid at the 1% significance level in nine of them.

In every variant, the pass-through remains higher at the ninetieth percentile compared to the twenty-fifth, with increases ranging between 44 and 147%. The inclusion of crisis dummies for the global financial crisis, the pandemic, and the war in Ukraine does not alter this structure ($p < 0.001$). Utilizing end-of-period exchange rates instead of period averages does not significantly change the outcome ($p < 0.001$). Excluding Turkiye, which was identified as having a determining effect in the cross-country stage, has no notable impact on the within-country results: the coefficient rises from 0.107 to 0.228 across the distribution, and equality is rejected at the $p < 0.001$ level. Excluding Colombia, the most extreme observation in terms of energy dependency, also does not change the result. Incorporating the geopolitical risk index in the subsample of fourteen countries where domestic series are available preserves the pattern ($p = 0.005$), and the same holds true for both shorter and longer lag structures.

When the sample is split in 2015, it becomes evident that regime dependence is concentrated in the second sub-period. Between 2006 and 2014, the increase from the twenty-fifth to the ninetieth percentile is 44%, and the equality test fails to reject the null hypothesis ($p = 0.233$); between 2015 and 2023, the increase is 142% ($p < 0.001$). Not only the precision but also the point estimates differ: the ninetieth-percentile coefficient is 0.175 in the first sub-period, whereas it is 0.302 in the second. Although the first sub-period includes the global financial crisis and the 2010–11 food price shock, this suggests that inflation expectations in these economies may have remained relatively well-anchored throughout the period. The second sub-period, on the other hand, encompasses the 2018 emerging market currency stress, the pandemic, and the war, during which time the anchoring is thought to have weakened in some countries within the sample. If regime dependence stems from firms adjusting their prices more readily under conditions where they expect inflation to be persistent, the degree of regime dependence is also expected to vary with the credibility of the monetary policy regime.

5 Discussion and conclusion

This study investigated the transmission of exchange rate shocks to consumer food prices across seventeen emerging market economies using monthly data over the 2006:01–2023:12 period. Cumulative pass-through coefficients were first obtained from country-specific distributed lag models and then related to structural country characteristics. A separate panel analysis examined how pass-through varies across the conditional distribution of food inflation using quantile regressions with country fixed effects. State dependence was then examined in two complementary ways: an explicit threshold specification using observed twelve-month food inflation, and quantile regressions characterising the conditional distribution.

The dependent variable of the study is a consumer-level food price index. In addition to the raw commodity component, retail food prices incorporate processing, packaging, distribution, rent, and labor costs. Because the proportion of the commodity component is relatively low, the strong link observed at the commodity level is dampened at the consumer level.

The nested specifications in Table 8 demonstrate that this is not a case where the commodity channel absorbs the energy effect. In an unconditioned specification, the aggregate cumulative oil effect is 0.008, which is statistically indistinguishable from zero. At the six-month horizon, energy is not transmitted to consumer food prices in this sample in an economically meaningful magnitude, either directly or through global commodity markets. The average cumulative pass-through is 0.213,

which falls within the range documented for emerging markets. In high-inflation economies, the food price index and the nominal exchange rate follow a common stochastic trend; if the evidence of cointegration is weak, a level regression measures this common trend rather than the actual pass-through.

Cumulative pass-through more than doubles when moving from the twenty-fifth to the ninetieth percentile of the distribution. This finding is consistent with the Taylor (2000) mechanism specifically for food prices: in a low-inflation regime, firms perceive cost increases as temporary and absorb a portion of the shock through their margins, whereas in a high-inflation regime, cost increases are transmitted rapidly. In the lower quantiles, the exchange rate effect is concentrated between the first and fourth lags before dissipating, whereas in the upper quantile, it remains significant even at the sixth lag. Pass-through is both larger and more persistent in a high-inflation regime.

The analysis points to four main findings. First, the exchange rate channel appears to play a substantially more prominent role than the energy channel in consumer food price movements. The cumulative effect of oil prices remains relatively small and is statistically insignificant at shorter horizons, although it becomes statistically detectable when the horizon extends beyond one year. Second, exchange rate pass-through appears to depend on the inflation environment in a nonlinear manner. It remains relatively stable at moderate inflation rates and becomes stronger as inflation rises, with formal threshold estimates suggesting that this change begins at annual food inflation rates of around 7 percent. At monthly horizons, however, the difference becomes statistically detectable only at higher inflation levels. The results are not driven by a single economy and remain broadly consistent across nine of the ten alternative specifications reported in Table 9. Third, there is little evidence that the relationship between global and domestic food prices weakens during periods of elevated inflation. An increase is observed in the upper conditional quantiles, but the difference is not statistically significant when inference accounts for cross-country dependence and is also absent when the inflation state is defined using observed inflation. Finally, cross-country differences in pass-through are not systematically associated with observable structural indicators such as food import dependence, energy dependence, or fertilizer import dependence. These findings suggest that changes in the domestic inflation environment may provide additional insight into the variation in exchange rate pass-through beyond that captured by the structural indicators considered in the analysis. The findings highlight the central role of macro-financial stability in food price stabilization. Because the exchange rate channel is the primary source of pass-through, the principal policy tools are exchange rate stability, the anchoring of inflation expectations, and financial instruments that allow importers to hedge against currency risk. Agricultural subsidies are complementary in nature and, on their own, are insufficient to keep food prices accessible.

Trade policy instruments do not address the primary channel of price formation. Export bans, quotas, and additional tariffs reduce producer incomes, thereby creating a risk of supply contraction in the medium term. Target 2.c of the Sustainable Development Goals specifically links price stability to the proper functioning of food commodity markets, and its monitoring indicator is constructed from national food price indices. Inventory management, licensed warehousing, and targeted social protection mechanisms reduce price volatility without distorting producer incentives.

5.1 Limitations and future research

The findings should be interpreted in light of several limitations. The energy price estimates primarily capture the global energy channel, as international benchmarks do not fully reflect country-specific energy and transportation costs. In addition, supply- and demand-driven oil price movements cannot be separately identified within the present framework. The estimated location of the inflation threshold also varies with the specification and time horizon, suggesting that the results are more informative about the nonlinear nature of exchange rate pass-through than about a single precise threshold. Finally, inference in the quantile analysis is subject to the difficulty of accounting for serial and cross-sectional dependence simultaneously, and these estimates are therefore treated as complementary to the threshold results. Future research could further examine these relationships using more disaggregated price and cost measures and explore the mechanisms through which inflation conditions influence exchange rate pass-through. Extending the analysis to household or product-level data may also provide a more detailed understanding of how these effects differ across consumer groups and food categories.

Data availability statement

The original contributions presented in the study are included in the article/Supplementary material, further inquiries can be directed to the corresponding author.

Author contributions

FU: Methodology, Writing – review & editing, Conceptualization, Data curation, Investigation, Validation, Writing – original draft, Formal analysis, Visualization, Project administration, Resources, Software.

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Supplementary material

The Supplementary material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fsufs.2026.1960606/full#supplementary-material

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