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International Commodity Prices Transmission to Consumer Prices in Africa*

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Abstract

Global commodity prices spikes can have strong macroeconomic effects, particularly in developing countries. This paper estimates the global commodity prices pass-through to consumer price inflation in Africa. Our sample includes monthly data for 48 countries over the period 2002m02–2021m04. We consider 17 commodity prices separately to take into account both the heterogeneity in price variations and the cross-correlations between them, and to depart from aggregate indices that use weights unrepresentative of consumption in African countries. Using local projections in a panel dataset, we find a maximum pass-through of 24%, and a long-run pass-through of about 20%, higher than usually found in the literature. We also consider country-specific regressions to test whether estimated pass-through are related to countries' observable characteristics.

JEL classification codes: C23, E31, F44, O11, Q02.
Keywords: Commodity prices, food prices, energy prices, inflation, pass-through, Africa.

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We find evidence that the pass-through is negatively correlated with the GDP per capita and the quality of transport infrastructure, and positively correlated with the share of food and energy in the consumption basket and the share of taxes on goods and services in government revenue. Net oil exporters, countries with larger energy subsidies and with a more independent central bank tend to have a lower pass-through. We further show that commodity-specific pass-through are correlated with the share of corresponding goods in the consumer basket.

1 Introduction

How do commodity prices pass-through to consumer prices? With the sharp increase in commodity prices observed worldwide from 2020, and even more in the beginning of 2022, this question has fostered renewed attention from policy-makers, especially among countries highly dependent on traded commodities. However, beyond the aggregate trend of commodity prices, a strong heterogeneity has been observed across commodities. For instance, according to the FAO and the World Bank, between the first semester of 2020 and the first semester of 2022, while the prices of food increased by about 50%, those of energy and fertilizers increased by about 200%. Within categories of commodities, the heterogeneity of price variations was also sizable. Within energy, over the same period, the price of natural gas was multiplied by six, while the price of oil was multiplied by two. Within food commodities, the prices of cereals increased by about 60%, while those of vegetable oils increased by more than 100%. Within cereals, the prices of rice decreased by about 10%, while those of wheat increased by more than 100%.

The African continent is likely to be both highly and heterogeneously exposed to this increase in global commodity prices. First, Africa is the continent with the highest share of food in total consumption worldwide (about 35 to 50% depending on the estimations), and in imports (13%, against about 8% worldwide). According to the Food and Agriculture Organization (FAO), about 35% of people in Sub-Saharan Africa faced severe food insecurity in 2020, and according to the IMF, in 2022, 12% of the population was in a situation of acute food insecurity (situation of crisis, emergency or famine), 30% of which fell into this situation within the two preceding years. Finally, the debt burden of African countries doubled during the 2010 decade, thus narrowing their financial margins to tackle the consequences of higher commodity prices. Yet, the price increases observed across commodities are unlikely to affect the continent's consumer prices equally, as the consumption shares of each commodity vary substantially, both on average across the continent and across countries. On average across the continent, according to the Global Consumption Database of the World Bank (documenting fine-grained consumption structures between 1996 and 2011 in Africa), the (unweighted) share of vegetable oils in food consumption in Africa is of 5%, while the (unweighted) share of cereals is of 30%, and that of energy in total consumption is of 6%. Within cereals, rice represents on average 10% of food consumption in Africa, while products derived from wheat represent 5%. Across countries in the continent, the share of food in total consumption ranges between 15% (in South Africa) and 70% (in Burundi). Similarly, the food consumption structure varies significantly between countries that, for instance, rely primarily on rice for their consumption of cereals (Sierra Leone, Madagascar, Liberia), or predominantly on wheat (such as São Tomé and Príncipe, Gabon or Mauritius). Assuming that, all else equal, commodities with a larger weight in consumption contribute more to inflation, estimated pass-through of commodity prices to inflation are likely to be particularly heterogeneous in Africa. However, evaluating such a hypothesis is only possible if the pass-through is estimated at the commodity level.

In this paper, we bring novel estimates of the pass-through of global commodity prices to consumer prices in Africa, both at the continent and country levels, that aim at addressing simultaneously these issues. To do so, we implement estimation strategies that take into account the heterogeneity of global commodity prices, both regarding their prices and their weight in the local consumption (either at the continent level, or at the country level). We do so by estimating the pass-through of 17 commodities among vegetable oils, cereals, sugar, energy and fertilizers, both using panel and country-by-country regressions. We argue that estimating commodity-specific pass-through is a theoretically appealing approach as, by taking into account commodity prices heterogeneity, it also allows the composition of consumer basket to play a role. Indeed, for a given commodity with a given global-to-local pass-through[1], its contribution to inflation will be higher if its share in total consumption is higher. Therefore, identifying separately the pass-through of each commodity to total consumer prices allows interpreting each of them as a product of the commodity's global-to-local pass-through (which can be as high as 100%, according to a recent study by Okou et al., 2022) and of the commodity's weight in total consumption. Such an interpretation is possible because, contrarily to most existing estimates, our empirical framework does not impose any *ex ante* weight on commodities.

Our approach departs from most of the contributions of the literature, which use aggregate indices of commodity prices. Using aggregate indices makes estimated pass-through challenging to interpret. Indeed, such an approach makes it is impossible to identify which of the underlying commodities contribute most to the pass-through. It is also likely to create biases in the estimation of the pass-through, as aggregate indices only capture the average of the underlying indices that are part of it, without capturing the heterogeneity of their dynamics. The biases in the estimated effects stemming from this channel might be both upward and downward. On the one hand, if substitution effects exist, using aggregate indices rather than separate commodity prices might yield higher pass-through: indeed, if the price of a single good rises while those of close substitutes do not, a shift of the demand away from the more expensive could dampen

[1]We define a global-to-local pass-through for a commodity as the transmission of the price of this commodity on the global market to the price of the same commodity on local markets. Such pass-through have been estimated, for instance, in Okou et al. (2022).

inflationary effects. Such dampening effects are less likely to occur if the prices of all substituable goods increase at the same time, a situation that might be better captured by aggregate indices. On the other hand, using an average of commodity prices is likely to induce a measurement error in commodity prices, which might generate downward biases. This measurement is likely to increase with the distance between the structure of the aggregating weighting scheme and that of the actual consumption structure at the local level. In the case of the commodity prices pass-through literature, since the weights of aggregated commodity prices depend on the share of each commodity in global trade, they are therefore unrepresentative of consumption on the African continent.[2] By being agnostic on the weight of each commodity in the consumer basket in Africa, our estimation strategy limits the risk of such a downward bias, while fully exploiting the heterogeneity of commodity prices. In fact, we show that our estimated pass-through are consistently and significantly higher than those estimated using the same commodity prices data, but aggregated *ex ante* with a fixed weighting scheme, suggesting that the overall bias arising from using aggregated indices is downward.

We estimate the pass-through of global commodity prices to consumer prices in Africa from 2002m02 to 2021m04 in 48 African countries. To do so, we use the World Bank *Pink Sheet* and resort to local projections (Jordà, 2005) at an 18-month horizon. Our main results are the following. First, using a panel data model, we estimate a long-run pass-through of commodity prices to inflation of about 20% on average over 12 months, with a maximum of about 24% after 7 months.[3] This pass-through is primarily driven by cereals and vegetable oils in the short-run, with increasing contributions of fertilizers in the longer-run. Energy prices have a much smaller impact on consumer prices, which is coherent with the fact that they are often administered in African countries. Comparing our main estimation strategy with one closer to the existing literature (i.e. using aggregate indices), we show that the latter yield pass-through that are close to those of the literature (which typically estimates pass-through of 5 to 15% of food commodity prices to inflation), but that our estimation yields consistantly higher estimates. In this framework, we also document several additional results, which help to interpret our main results. First, we compare the pass-through between positive and negative shocks, and find that both entail significant pass-through, suggesting that our results are not driven by a specific type of shock. However, the pass-through are slightly asymmetric between positive and negative shocks: while the

[2] In this context, observing a higher pass-through in a specific area compared to another might either mean that its consumer prices react more than in other areas, or that its consumption structure is closer to the weighting scheme of the commodity prices index than other areas.

[3] Throughout the paper, we define the long-run pass-through as the value taken at the end of the projection horizon, namely after a year and a half.

response of prices to a negative shock appears smooth and moderate during the first year (it reaches 17% after 7 months), the response of prices to a positive shock is muted in the first three months (and even slightly negative), before increasing strongly to 35% between months 7 to 10, and then decreasing smoothly to about 20%. However, the pass-through of negative shocks increases strongly in the last months of the horizon (until reaching -40% after 18 months), suggesting longer-lasting effects of negative shocks. Second, we document an exchange-rate pass-through of about 10%, which is much smaller than estimated in previous papers (40% in Razafimahefa, 2012): this suggests that a substantial share of the exchange rate effect estimated without controlling for commodity prices is likely to embed effects due to the latter.

In a second part of the analysis, we use country-wise local projections, in order to explore the role of country-specific characteristics, and notably of cross-country heterogeneity in terms of consumption structure. We first show that such an approach yields an aggregate response very close to the one estimated in the panel specifications. We then test the correlations of the pass-through with a wide array of observed covariates and find that only a few of them explain the cross-country variations of pass-through. Namely, we show, as emphasized in previous contributions, that countries with higher pass-through are also countries where the share of food and energy in total consumption is higher, and where GDP per capita is lower. We also find that the pass-through is lower in countries with a higher level of energy subsidies, among net commodity exporters and among countries with a lower share of taxes on goods and services in government revenue. Additionnally, we provide suggestive evidence that the pass-through decreases with central bank independence (especially in flexible exchange rate arrangements). However, we do not find evidence of significant correlation with the degree of openness of the economy and the polity score of the country.

Finally, leveraging on the main innovation of our methodology, we provide evidence of a correlation between commodity-wise pass-through and the share of the corresponding commodity in the consumer basket. Importantly, we find that this correlation is driven primarily by within-country variations, and that it is not significant across countries. More specifically, within a given country, commodities representing a higher share of the consumption basket tend to have a higher pass-through, but for a given commodity, countries with higher shares of such commodity in the consumption basket do not necessarily have higher pass-through.

Our paper is related to an extended literature that estimates the pass-through of global commodity prices to local consumer prices. Our main contribution to this literature is to adapt our modelling strategy to the fact that consumption structures across countries and global commodity prices dynamics are heterogeneous. The contributions the closest to ours on the topic are Furceri et al. (2016), Bekkers et al. (2017) and Gelos and Ustyugova (2017), which use various methodologies. While Bekkers et al. (2017) and Furceri et al. (2016) use food commodities, Gelos and Ustyugova (2017) use both aggregate food and energy commodities. Bekkers et al. (2017) focus on food CPI, while Gelos and Ustyugova (2017) focus on total CPI, and Furceri et al. (2016) focus on both. Finally, while Bekkers et al. (2017) and Gelos and Ustyugova (2017) use country by country regressions, Furceri et al. (2016) use panel data analysis. Overall, in these contributions, the estimated pass-through of global commodity prices to consumer prices in developing countries range between 5 and 15%. They show *ex-post* that the estimated pass-through are correlated with several factors such as share of food in CPI (Furceri et al., 2016; Gelos and Ustyugova, 2017), GDP per capita (Bekkers et al., 2017), central bank independence and governance score (Gelos and Ustyugova, 2017), or trade policy measures (Bekkers et al., 2017). Bekkers et al. (2017) also argue that, controlling for GDP per capita, the pass-through is 10% lower in African countries because of higher trade costs.

We go one step further and identify separately the effects of various commodities. From this standpoint, our paper is also close to the recent contribution of Okou et al. (2022), which documents a pass-through close to unity between global food prices and local staple food prices, focusing on the 5 top staples in 15 Sub-Saharan African countries (namely maize, rice, cassava, wheat and palm oil). The latter results confirm the importance of identifying the effects of food prices commodity by commodity, in order to avoid underestimating them. However, our approach aims at estimating the effects on total inflation. To do so, our choice is to focus on total consumer prices (since commodity prices can have indirect effects on other components, especially in the longer run), and to combine food commodities (cereals, vegetable oils, sugar) with non-food commodities (energy, fertilizers). Compared to the aforementioned contributions, our approach has the advantage of providing a full decomposition of the total pass-through across commodities, at both the continent and the country level. It also yields significantly higher pass-through compared to the existing estimates. We argue that this is mostly related to the estimation methodology, while the fact of using an expanded set of commodities plays a more minor role (namely, while fertilizers, which are not studied in the aforementioned papers, contribute to a higher pass-through in our analysis, it explains only a limited fraction of the gap with existing studies). Finally, these improved estimates remain correlated with traditional factors that were found to affect commodity prices pass-through to inflation in the literature (such as the share of food and energy in total consumption, GDP per capita), and allow to document a significant correlation between the pass-through of specific commodities with the share of corresponding products in food consumption.

Finally, our study also relates more broadly to a large literature studying the determinants of price dynamics. Typical models studying the determinants of inflation tie prices to real activity measures, often in a Phillips curve framework. However, several measures of real economic activity used in Phillips curve settings (such as unemployment rates or output gaps) are more challenging to interpret in the African context, which is often characterized by a high degree of informality. Furthermore, as our setting relies on monthly data, tying consumer price data with economic activity indicators is particularly difficult, as the latter are often available at either an annual or a quarterly frequency in Africa. To overcome this issue and control for real factors at a monthly frequency, we control for several factors which were found to have a significant impact on inflation in emerging or developing countries. Specifically, several strands of the literature have shown that inflation is likely to be strongly affected by the occurrence of natural phenomena (Faccia et al., 2021 for heatwaves, Parker, 2018 and Heinen et al., 2019 for natural disasters), by the exchange rate (Razafimahefa, 2012), and by the occurrence of conflicts (Koren and Bagozzi, 2016; Martin-Shields and Stojetz, 2019; Bellemare, 2015; Weinberg and Bakker, 2015; Weezel, 2016). As these factors can be quantified with data that can readily be matched with monthly price indices, we therefore include them as control variables in our regressions. Specifically, we control for natural disasters intensity, the USD exchange rate and the intensity of civil conflict.

The remainder of the paper is structured as follows. Section 2 describes the data we use and shows some stylized facts about consumption baskets in Africa and variations of commodity prices worldwide in the last two decades. Section 3 describes the empirical strategies we use to estimate the pass-through of global commodity prices to consumer prices in Africa. Section 4 presents the results obtained in the specification using panel data and discusses the results in light of the existing literature. Section 5 presents the results obtained in the country-by-country regressions and discusses potential transmission channels. Section 6 concludes.

2 Data and Stylized Facts

We construct a country-level dataset covering 48 African economies at a monthly frequency during the period 2002m02–2021m04 to assess the pass-through of global commodity prices to consumer prices in Africa. Appendix Table A.1 lists the countries included in the sample with their respective share in the sample based on their 2021 purchasing power parity real GDP, and Appendix Figure A.1 shows the regional division of the sample. The sample selection is based on data availability. Appendix Table A.2

lists all the data sources used in this paper.

The main dependent variable is the growth rate of the Consumer Price Index (CPI) between month $m-1$ and month $m+h$. We construct it using data in Ha et al. (2021). For a country i and month m, we write:

$$g_{CPI_{i,m-1;m+h}} = \frac{CPI_{i,m+h} - CPI_{i,m-1}}{CPI_{i,m-1}}$$

The explanatory variables are the month-over-month (MoM) global commodity prices growth, constructed from the World Bank's *Pink Sheet*. We include 17 commodities comprising energy (crude oil, coal – South Africa, and a natural gas index), cereals (groundnuts, soybeans, maize, rice – Thai 05 – 5% broken – and wheat), vegetable oils (rapeseed oil, sunflower oil and palm oil) and fertilizers (phosphate rock, DAP, TSP, urea and potash), as well as sugar. The following principles apply to the choice of commodities. First, we include commodities that relate directly to food, energy or fertilizers consumption, in order to make our estimates more comparable to the literature. Therefore, we drop items such as wood, metals, cotton, rubber and tobacco. Regarding fertilizers, which indirectly affect the prices of food, we keep all those listed in the dataset. Regarding energy, we keep all types of commodities reported in the Pink Sheet. Regarding natural gas and crude oil, we keep average values across several types of markets (the US, Europe and Japan for natural gas) or goods (Brent, WTI and Dubai indices), in order to take into account the possibility of different supply sources across countries. Regarding coal, we include the price of South-African coal rather than Australian coal. Regarding food, given the variety of items and the necessity to maintain parcimony in the estimation, we focus on 9 items among cereals, vegetable oils and sugar for two reasons. First, these 9 items represent a sizable share in total consumption: according to the Food Balance Sheet data from the FAO, on average between 2010 and 2019, they represent 50% of calory intakes in Africa. Second, contrarily to several types of food commodities, Africa is a strong net importer of the main globally traded cereals and vegetable oils, as lots of them are not produced locally. Focusing on cereals and vegetable oils therefore implies the exclusion of goods considered as beverages in the World Bank classification (cocoa, coffee and tea), meat or seafood (beef, chicken, sheep, shrimps) and fruits (banana, orange). Overall, according to the Food Balance Sheet data, these items represent a more limited share of calory intakes (5% on average), and as regards coffee and cocoa, they are heavily produced in some African countries. Among cereals, we exclude sorghum and barley (both of them entailing discontinued series). Among vegetable oils, we exclude coconut oil. Finally, some ties can exist in cases where a crop can correspond either to a plant-type commodity or to a vegetable oil: this is the case for groundnut (which is listed both as groundnut or groundnut oil) and soybeans (which is listed as soybeans, soybeans oil or soybeans meal). In both cases, we select the type good that appear to be the least transformed (namely soybeans and groundnut). Finally, in the case of rice, for which 3 types of Thai rice and one type of Vietnamese rice are listed, and which strongly comove, we select the 5% broken Thai rice.

The MoM growth rate of commodity k's price is computed as:

$$G_{P_{k,i,m-1;m}} = \frac{P_{k,i,m} - P_{k,i,m-1}}{P_{k,i,m-1}}$$

We include control variables from several sources. We use IMF's IFS database to obtain the nominal exchange rate in local currency units per USD (therefore, an increase corresponds to a depreciation). We also use the IFS database to obtain a proxy for the monetary policy rate, constructed as the average of the deposit and lending rates due to the availability of these variables.

We include a measure of conflict by retrieving monthly fatalities from battles, protests and riots from the ACLED database (Raleigh et al., 2010). We first construct a rate of fatalities per 100,000 inhabitants and then compute a measure of conflict intensity by dividing this rate by its standard deviation, denoted $\sigma_{Fatalities\ share}$. Our measure is then:

$$Conflict_{i,m} = \frac{Fatalities\ rate_{i,m}}{\sigma_{Fatalities\ rate,i}}$$

with:

$$Fatalities\ rate_{i,m} = \frac{Fatalities_{i,m}}{Population_{i,t}} \times 100,000$$

Finally, we also construct a measure of climate-related natural disasters' intensity inspired from Parker (2018). We obtain data on total death and persons affected resulting from climate-related natural disasters from EM-DAT (CRED, 2022). Climate-related natural disasters include droughts, extreme temperatures, floods, glacial lake outbursts, landslides, mass movements, storms and wildfires. We first compute climate-related natural disasters' impact as:

$$CRND\ impact_{i,m} = \frac{Death_{i,m} + 0.3 \times Affected_{i,m}}{Population_{i,t}} \times 100,000$$

We then divide this variable by its country-specific standard deviation $\sigma_{CRND\ impact,i}$ to obtain our measure of climate-related natural disasters' intensity:

$$CRND\ intensity = \frac{CRND\ impact_{i,m}}{\sigma_{CRND\ impact,i}}$$

Table 1 provides descriptive statistics for each variable and the entire sample.

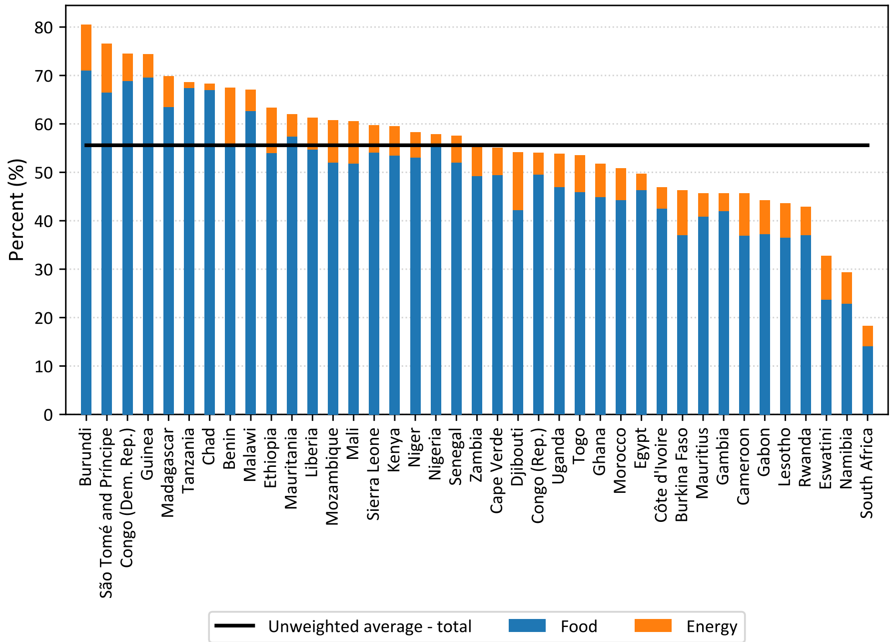
Table 1: Summary Statistics

Variable	Obs.	Mean	Std. Dev.	Min.	Max.
g_{CPI}	10,546	0.005	0.016	-0.612	0.645
$gp_{Crude\ Oil}$	231	0.010	0.095	-0.396	0.444
$gp_{Coal\ (South\ Africa)}$	231	0.007	0.073	-0.258	0.227
$gp_{Natural\ Gas\ (Index)}$	231	0.006	0.095	-0.327	0.339
$gp_{Groundnut}$	231	0.005	0.054	-0.319	0.206
$gp_{Palm\ oil}$	231	0.006	0.061	-0.230	0.211
$gp_{Soybeans}$	231	0.006	0.054	-0.239	0.174
$gp_{Rapeseed\ oil}$	230	0.006	0.048	-0.160	0.141
$gp_{Sunflower\ oil}$	223	0.006	0.057	-0.220	0.182
gp_{Maize}	231	0.007	0.062	-0.217	0.246
$gp_{Rice\ (Thai,\ 05)}$	231	0.006	0.060	-0.161	0.527
$gp_{Wheat\ (US,\ HRW)}$	231	0.006	0.068	-0.197	0.258
$gp_{Sugar\ (world)}$	231	0.006	0.074	-0.265	0.218
$gp_{Phosphate\ rock}$	231	0.009	0.121	-0.545	1.243
gp_{DAP}	231	0.009	0.079	-0.376	0.405
gp_{TSP}	231	0.008	0.071	-0.372	0.353
gp_{Urea}	231	0.012	0.123	-0.500	1.046
gp_{Potash}	231	0.007	0.095	-0.415	0.708
$\Delta log(e_{USD})$	11,073	0.002	0.027	-0.255	0.631
$CRND\ intensity$	11,088	0.249	1.097	0.000	22.124
$Conflict$	11,088	0.330	1.237	0.000	24.178
$\Delta log(i_{MPR})$	11,088	-0.004	0.081	-2.690	0.447

Note: g denotes the month-over-month growth rate and Δ denotes the first difference. The interest rate i_{MPR} is expressed in percents. e_{USD} denotes the nominal exchange rate expressed in local currency units per USD: an increase in e_{USD} denotes a depreciation.

We also collect data about the structure of household consumption in Africa. These data are taken from the Global Consumption Database of the World Bank, which includes 39 African countries between 1996 and 2011. Figures 1 to 3 represent some stylized facts about consumption in Africa. While the share of food in consumption in Africa is typically higher than in the rest of the world, it is highly heterogeneous (Figure 1). The (unweighted) average share of food in consumption was 49% according to the Global Consumption Database of the World Bank, which includes 39 African countries between 1996 and 2011. The lowest share observed in the data is in South Africa (14%), while the highest share is observed in Burundi (71%), reflecting heterogeneity in income per capita. In all observed countries, the share of energy is much lower than the share of food, representing only 6.4% of the consumption basket on average. The highest share of energy is observed in Djibouti (12.0% of the consumption basket) while Tanzania has the lowest share (1.2%).

Figure 1: Food and Energy Shares in Total Consumption in Africa

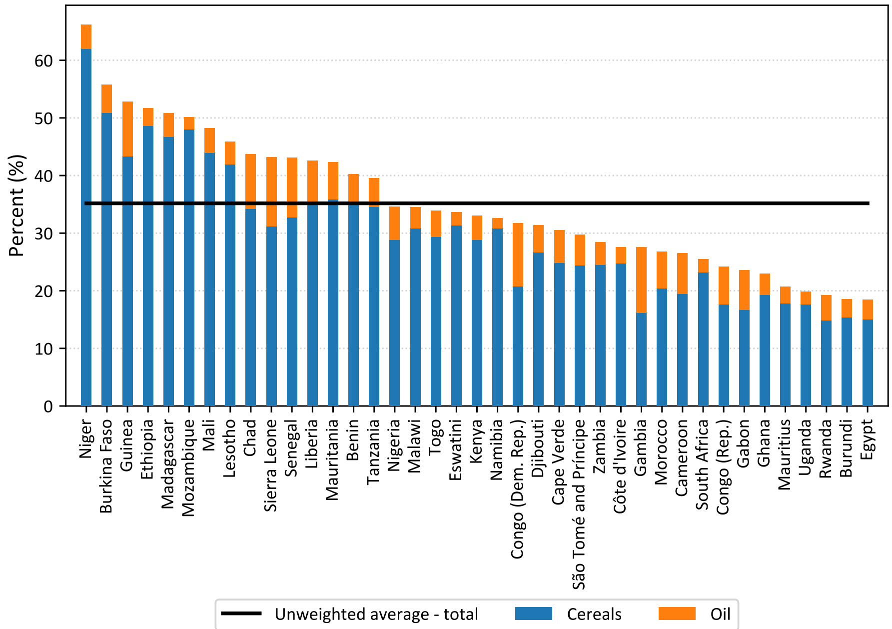


Note: Elaborated by the authors from the World Bank's Global Consumption Database.

Beyond these observations about the size of the food and energy components in the consumption basket, heterogeneity is high regarding the respective importance of each type of commodity in the food consumption basket. Figure 2 shows that the share of cereals in food consumption ranges from about 15.0% in Egypt to more than 62.0% in Niger, with an average of 35.2% in the 39 countries for which data is available. The share of oils ranges from a minimum of 1.8% in Namibia to 12.0% in Sierra Leone, with an (unweighted) average of 5.3% in the 39 countries.

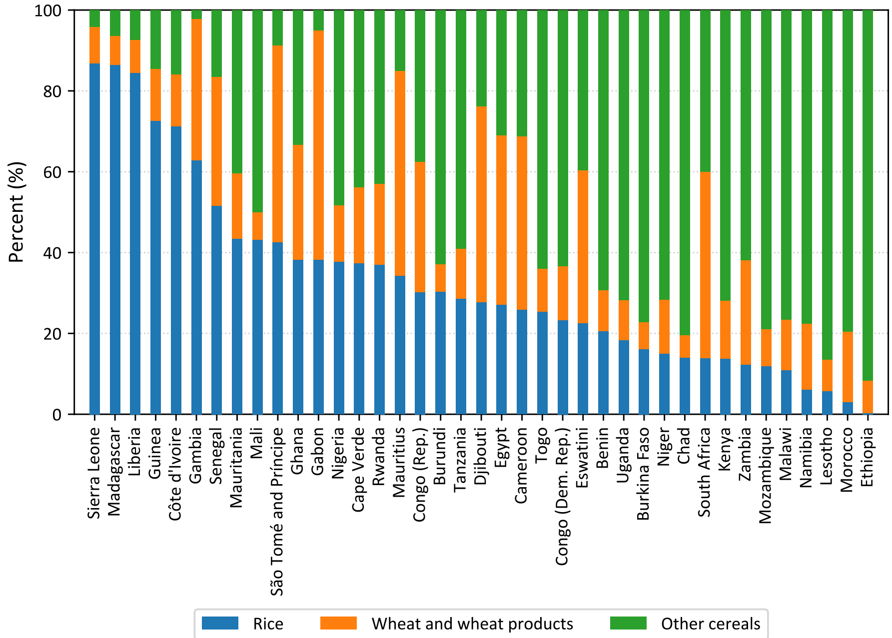
This high heterogeneity is also prevalent within each type of commodity. Figure 3 focuses on the cereal consumption basket and shows a marked heterogeneity between countries where rice is predominant and represents more than 50% of total cereal consumption (such as in Sierra Leone, Madagascar, Liberia, Guinea, Cote d'Ivoire, Gambia or Senegal) and those countries where wheat is predominant (such as São Tomé and Príncipe, Gabon, Mauritius, Egypt, Djibouti, Cameroon, Eswatini or South Africa). The share of other cereals is superior to 50% of the cereal consumption basket in 17 countries out of 39, with an unweighted average 46.2% in the 39 countries.

Figure 2: Cereal and Oil Shares in Food Consumption in Africa



Note: Elaborated by the authors from the World Bank's Global Consumption Database.

Figure 3: Cereal Consumption Structure in Africa



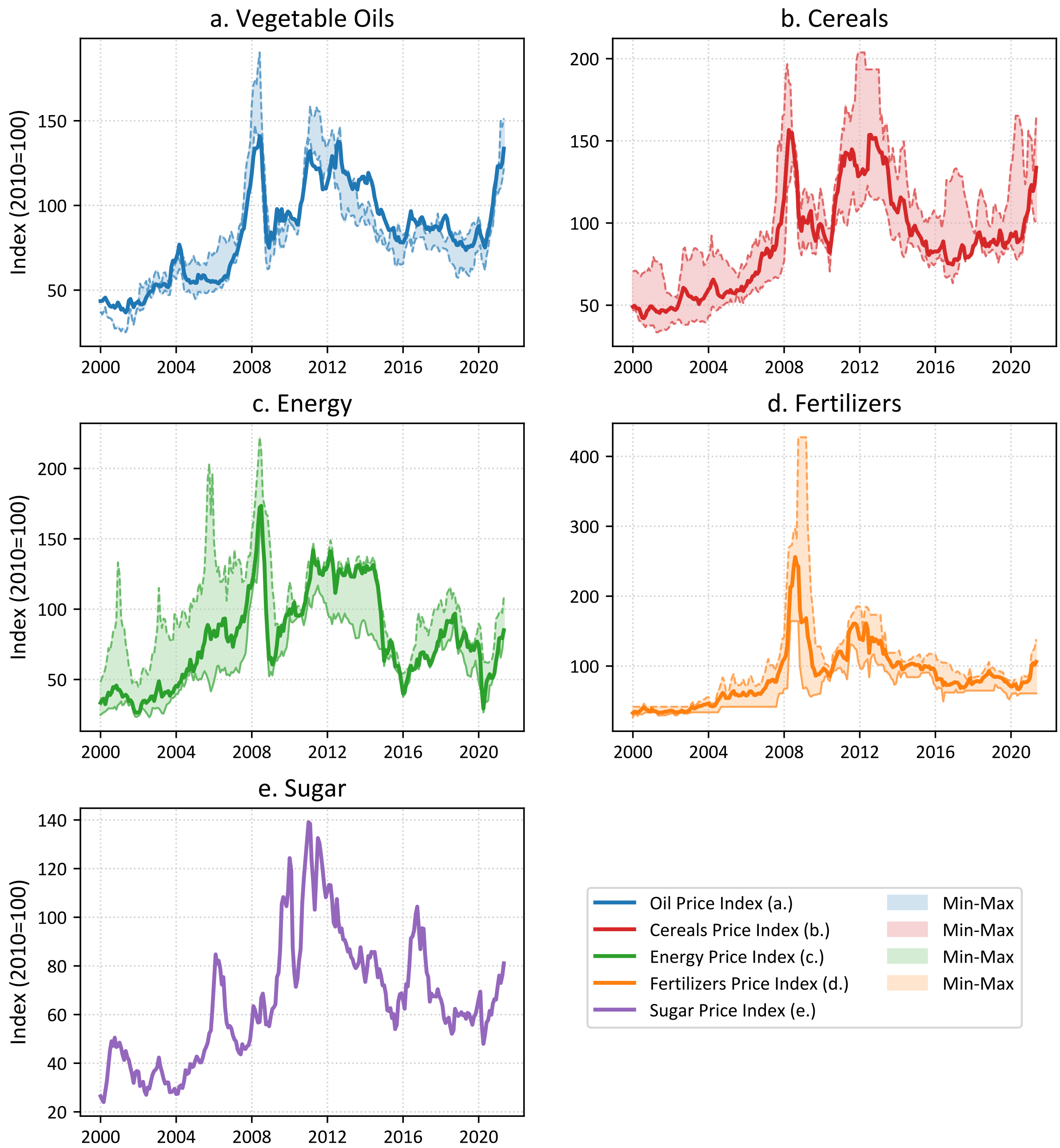
Note: Elaborated by the authors from the World Bank's Global Consumption Database.

In this context characterized by high consumption heterogeneity, using an aggregate world food price index as a dependent variable to study the commodity prices pass-through to consumer prices is likely to yield biased estimates, because it would impose each commodity a weight corresponding to its share in world trade, rather than to its share in the local consumption basket. The relevance of using a disaggregated approach is all the more important if commodity prices are not fully correlated, as is the case in our sample. We document this heterogeneity in the following Figures. First, Figure 4 shows the dynamics of global commodity prices and aggregate indices. Each series has been rebased and is equal to 100 in 2010. The data lead to several observations. First, they allow to visualize the three recent food crises of 2007–2008, 2011 and from the second semester of 2020 until the end of the sample's period. Second, the minimum and maximum commodity prices dynamics seem to be correlated with the aggregate index in each category. Third, each category of commodities is characterised by marked prices variability and heterogeneity. Energy and fertilizer prices can have 4-to-1 ratios between the maximum and minimum values in our sample, and this ratio reaches 2-to-1 for cereal prices.

Figure 5 documents the instanteneous correlations between the 17 commodities included in our sample. Four main facts stand out. First, the prices of vegetable oils are strongly correlated to each other, with correlation coefficients close to 60%. Second, the prices of maize, soybeans and wheat are strongly correlated, with positive correlation between 42% and 58%. However, the price of rice is hardly correlated with that of other cereals (it is instead much more correlated with the prices of fertilizers). Third, most of fertilizers' prices are strongly correlated with each other (with correlations ranging from 25% to 61% for DAP, TSP and urea, and a coefficient of 33% between phosphate and potash). Finally, the prices of cereals and of vegetable oils are positively correlated (with correlations ranging from 23% to 50% for soybeans, wheat and maize, with the three vegetable oils we study).

However, one might worry that cross-correlations of commodity prices do not occur only instantaneously. In particular, it might be possible that correlations between the prices of fertilizers and those of cereals or vegetable oils are correlated with a lag, the former being an input in the production of the latter. The same could also be true for the correlation of natural gas prices and fertilizers'. In Figure 6, we document pairwise dynamic correlations evaluated over a rolling window of 13 months (from 6 months backward to 6 months forward), and display all pairs for which a correlation coefficient of at least 30% is observed at least once. We find that, for about 75% of these pairs of variables, the highest correlation occurs instantaneously. This is particularly the case for the pairs of variables with the highest observed correlations. Only a few pairs of

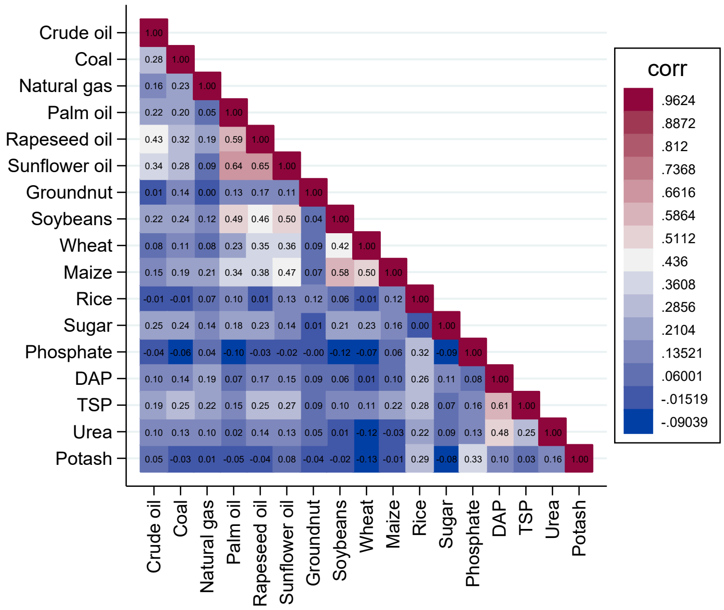
Figure 4: Global Commodity Prices



Note: Elaborated by the authors from the World Bank's Pink Sheet Database. The straight lines denote aggregate indices, as reported in the World Bank's Pink Sheet, and the shaded area report the difference between the maximum and minimum values for the 17 commodities used in this paper. The aggregate index can be out of the shaded area because it incorporates more series than those used in this paper. The series for each commodity price has been rebased such that it is equal to 100 in 2010.

variables have maximum correlation that occur with a lag, most of them involving fertilizers (TSP and DAP) and cereals, with a lag of 3 months.[4]

Figure 5: Correlation of commodity prices

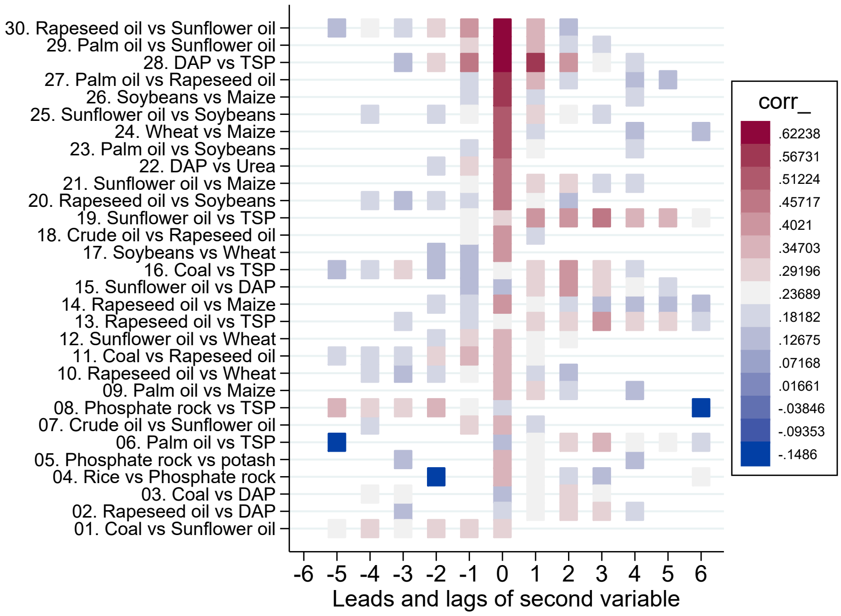


Note: Elaborated by the authors from the World Bank's Pink Sheet.

These stylized bear have three implications for our empirical specification. First, there is a significant heterogeneity in the price variations of commodities, as most observed instantaneous correlations are positive but small, with typical values around 10%. This highlights the need to identify separate effects for each of these commodities, in order to identifiy their respective contributions. Second, there are cross-correlations between the prices of some commodities, both within a type of commodity (*i.e.* within cereals, vegetable oils and fertilizers) and across types of commodities (*i.e.* between cereals and vegetable oils). This sheds light on the fact that, if one wants to identify separately the effect of different commodities, this cannot be done properly without controlling for the price variations of other commodities. The estimation framework must therefore ensure that the effect of each commodity is estimated net of the effects of other commodities that might comove at the same time. Finally, most of the observed correlations between commodity prices are instantaneous: this suggests that a specification controlling jointly for instantaneous correlations is likely to partial out most of the comovements between commodities.

[4]However, in these cases the instantaneous prices of cereals seem to be correlated with future values of fertilizers.

Figure 6: Correlation of commodity prices - Dynamic



Note: Elaborated by the authors from the World Bank's Pink Sheet. Only pairs of variables with a correlation of at least 30 % are displayed. Displayed coefficients are all significant at least at the 5% level.

3 Empirical Framework

We use the local projections method introduced in Jordà (2005) to estimate the pass-through of global commodity prices to consumer prices. We first use a panel model and separately estimate Equation (1) for horizons $h = 0, 1, ..., 18$:

$$g_{CPI,i,m-1;m+h} = \sum_{k \in K} \theta_k^h \, g_{P_{k,m-1;m}} + \gamma_1^h \, \Delta log(e_{USD,i,m-1;m}) + \gamma_2^h \, CRND\ intensity_{i,m} + \gamma_3^h \, Conflict_{i,m}$$
$$+ \gamma_4^h \, \Delta log(i_{MPR,i,m-1;m}) + \delta_i^h + \delta_{cm}^h + \delta_t^h + \delta_{i,cm}^h + \delta_{i,t}^h + \varepsilon_{i,m}^h \quad (1)$$

where i denotes the country, m the month and K a vector of 17 commodities: crude oil, coal – South Africa, natural gas, groundnuts, soybeans, maize, rice – Thai 05, wheat, rapeseed oil, sunflower oil, palm oil, phosphate rock, DAP, TSP, urea and potash, sugar. $g_{CPI,i,m-1:m+h}$ denotes the total growth of the consumer price index between months $m-1$ and $m+h$, and $g_{P_{k,m-1;m}}$ the MoM growth rate of commodity k's price between months $m-1$ and m. Control variables include the MoM growth rate of the nominal exchange rate (expressed in local currency units per USD) between month $m - 1$ and m, proxied by $\Delta log(e_{USD,i,m-1;m})$, the intensity of climate-related natural disasters (*CRND intensity*), the intensity of civil conflicts (*Conflict*) and the percentage MoM variation in the monetary policy rate between months $m-1$ and m, proxied by $\Delta log(i_{MPR,i,m-1;m})$.

Our specification includes a series of horizon-specific fixed effects to control for unobservable factors that might drive inflation. We include country fixed effects, denoted δ_i^h, to control for time-invariant country characteristics such as economic policy effectiveness and credibility, and (calendar) month and year fixed effects, denoted δ_{cm}^h and δ_t^h respectively, to capture common shocks such as the international business cycle.

We also include country-specific calendar month fixed effects ($\delta_{i,cm}^h$) to capture country-specific seasonality patterns that are fixed across years, such as national holidays, and country-specific year fixed effects ($\delta_{i,t}^h$) to capture country-specific shocks such as a bad harvest and oil and gas discoveries.

We then perform country-by-country regressions following a similar approach and separately estimating Equation (2) for horizons $h = 0, 1, ..., 18$:

$$g_{CPI,m-1;m+h} = \sum_{k \in K} \theta_k^h \, g_{P_{k,m-1;m}} + \gamma_1^h \, \Delta log(e_{USD,m-1;m}) + \gamma_2^h \, CRND\ intensity_m + \gamma_3^h \, Conflict_m + \gamma_4^h \, \Delta log(i_{MPR,m-1;m}) + \delta_{cm}^h + \delta_t^h + \varepsilon_m^h \tag{2}$$

where the variables and subscripts are denoted as in Equation (1). We include (calendar) month fixed effects, δ_{cm}^h, to capture seasonality patterns that are fixed across years and year fixed effects, δ_t^h, to control for domestic and international shocks such as a bad harvest and the international business cycle.

We include all commodity prices growth rates separately in both the panel and the country-specific specifications to take into account the heterogeneity in price variations and the cross-correlations between commodity prices. As indicated above, given the correlations structure of commodity prices, a specification controlling only for simultaneous correlations is likely to partial out most of the correlations existing between commodities. However, since some correlations take up to 3 months to reach their maximum value, in a robustness test, we control for up to 3 lags of each commodity.

Importantly, while our baseline panel regression alows cross-commodity heterogeneity to play a role (both in terms of prices and in terms of average weight in the consumption basket at the continent level), it does not allow to estimate the effect of cross-country consumption heterogeneity. To test this heterogeneity, we run country-specific regressions, which allows us to correlate estimated country-specific pass-through with country-specific characteristics (and notably with country-specific consumptions structures). Our baseline specification is however the panel specification, as it helps recovering more easily confidence intervals, and it is better suited to run additional tests of asymmetry.

It is worth noting that the types of commodities we consider might not affect consumer prices through the same channels. While cereals and vegetable oils prices are likely to be transmitted to consumer prices essentially through a direct channel, energy prices might be transmitted both directly (through effects on the price of cooking fuel or transports) or indirectly (as it is also an intermediary good that affects the cost of production in the food and manufacturing sector), while fertilizers prices are likely to be transmitted essentially indirectly (through their effects on harvests). An ideal approach would combine our estimates on consumer prices with effects on producer prices, in order to identify the diffusion of the pass-through along the production chain. However, to the best of our knowledge, producer prices series are not available for African countries as consistently and frequently as consumer prices.

Finally, it is also important to acknowledge that not all commodity prices are equally exogenous to consumer prices in this setting. While most African countries are net importers of the majority of the commodities under scrutiny, some variations exist regarding their dependence on imports. Palm oil is widely cultivated in Western Africa (Ivory Coast, among others) and several African countries are net oil exporters (CEMAC, Nigeria, Angola), or of coal (South Africa). Additionally, according the FARM report, while 38 African countries depend imports for the totality of their wheat consumption, some of them have a large production that can cover part of their consumption (South Africa and Egypt, among others). These large productions could potentially affect simultaneously both domestic and, more modestly, international prices, thus affecting the estimates. While we acknowledge the risk of such a bias, instrumenting commodity prices variations in such a setting so as to recover exogenous variations would prove particularly challenging, since a different instrument should be found for each commodity. Importantly for the interpretation of our results, such instrumentation does not appear to have been implemented in the contributions we compare our results to.[5]

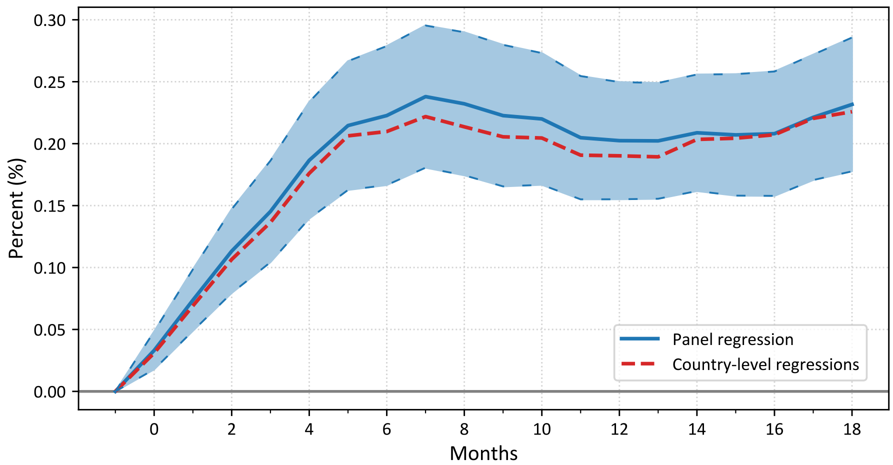
[5]Alternative approaches could have been considered to study the effects of commodity prices on local prices, in the spirit of Okou et al. (2022). One of them could consist in including consumption shares of each commodity in the regression, in order to partial out their effects. The estimated effect would therefore capture a form of global-to-local pass-through, albeit imperfectly. However, such an approach is difficult to implement in practice. Indeed, if we used weights based on estimated consumption baskets, they would only be mapped imperfectly to global commodities (as the best survey we have access to is less detailed than the classification of 17 commodities we uses), and since they are available only on a cross-section basis, they would be absorbed in the country fixed effect. If, to the contrary, we used weights based on international trade of commodities, we could have a well-defined weight structure

4 Panel Specification Results

4.1 Main Results

The main result of the panel specification is represented in Figure 7. In this figure, we plot, for each horizon, the sum of the 17 coefficients estimated (which gives the total cumulated response), as well as the 95% confidence interval. This cumulated response therefore corresponds to the reaction of consumer prices to a simultaneous shock of 1% on all commodities. We observe that consumer prices in Africa react progressively to such a shock: the pass-through is complete after about 7 months, when it reaches a maximum of 24%. It then remains broadly stable until the end of the projection horizon.

Figure 7: Estimated Effect of a 1% Increase in Commodity Prices on Consumer Prices

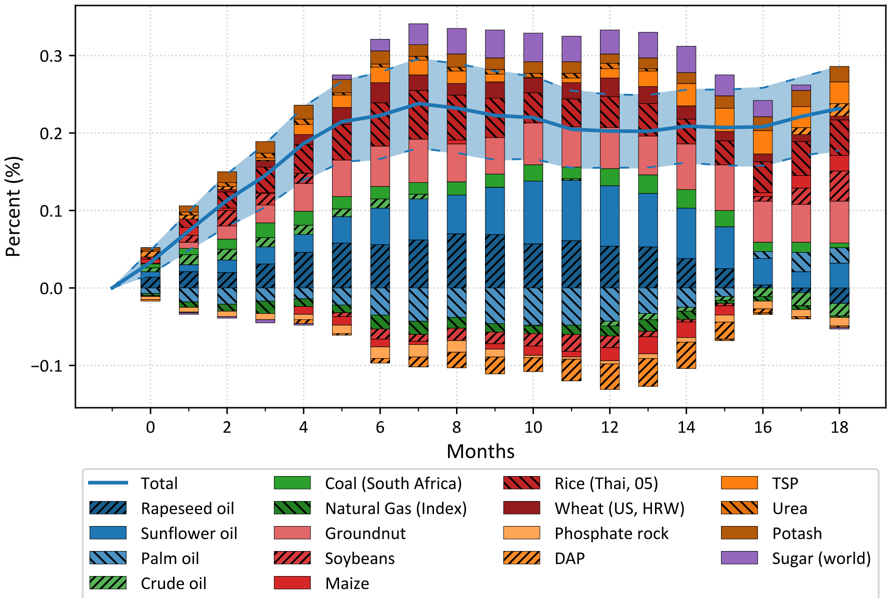


Note: Impulse response of total CPI to a simultaneous 1% shock on the prices of 17 commodities in 48 African countries, estimated between 2002m02 and 2021m04, with a weight corresponding to real GDP at purchasing power parity as of 2021. The blue curve corresponds to results of a panel regression, the blue area corresponds to the 95% confidence interval of this regression, and the red dotted line corresponds to the aggregation of 48 impulse responses estimated at the country-level.

Given that the total impulse response function results from a sum of coefficients estimated for each commodity, we are able to decompose the contributions of each commodity to the total response. Figure 8 reports these results (the underlying estimates by products are reported in Appendix Table B.1). Four main messages emerge from this figure. First, vegetable oils and cereals explain much of the positive reaction in the short run: this is particularly true of rapeseed oil (maximum pass-through of

at the country level, but we would have no guarantee that estimated weight would be representative of household consumption at the local level. We therefore prefer not to include these weights in the regression, and to use them only in the country-by-country regressions. Finally, not partialling out the structure appears informative, as the estimated effect can be interpreted directly as a contribution to variation of headline consumer prices.

Figure 8: Estimated Effect, Decomposition by Product

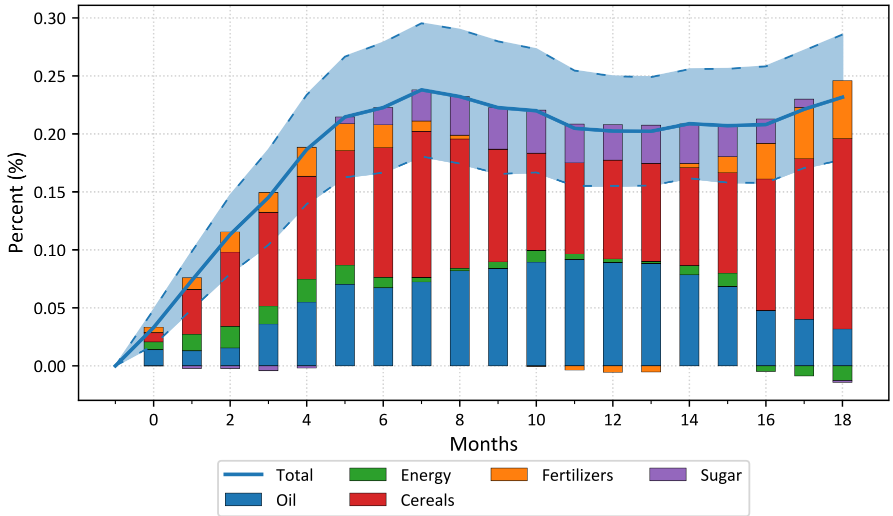


Note: Impulse response of total CPI to a simultaneous 1% shock on the prices of 17 commodities in 48 African countries, estimated between 2002m02 and 2021m04, with a weight corresponding to real GDP at purchasing power parity as of 2021. The blue curve corresponds to results of a panel regression, the blue area corresponds to the 95% confidence interval of this regression. The stacked bars correspond to the impulse response of total CPI to each shock on the 17 commodities.

7.0% after 8 months), sunflower oil (maximum pass-through of 8.1% after 10 months), rice (maximum of 6.3% after 7 months), groundnut (maximum of 5.9% after 14 months), wheat (maximum of 2.6% after 6 months) and sugar (maximum of 3.7% after 10 months). Second, the prices of energy commodities have small effects on consumer prices: crude oil prices have a maximum pass-through of 1.4% after two months, and coal have a maximum pass-through of 2.4% after 13 months. This may be due to the high prevalence of administered prices in the energy sector in Africa. Third, while fertilizers have small and heterogeneous effects in the short run (with small and positive effects of potash and insignificant or negative effects for other fertilizers), their overall effect increases in the longer run, until being neatly positive at the end of the horizon (3.0% for TSP after 14 months, and 2.1% for potash after 19 months). Finally, some negative contributions emerge (natural gas, maize, phosphate rock, natural gas, palm oil), but most of them are typically below 2% in absolute value, with the exceptions of palm oil and DAP, which respectively reach a minimum pass-through of -4.8% after 10 months and -3.6% after 13 months.

We next group the products together into five categories: vegetable oils, energy, cereals, fertilizers and sugar. The results reported in Figure 9, and in Appendix Table B.2, indicate that the pass-through of cereals reaches a first peak at 12.6% after 7 months, then decreases before increasing again until reaching a maximum of 16.4% after 18 months. Regarding vegetable oils, their total pass-through reaches a maximum of 9.2% after 11 month. The pass-through of fertilizers first reaches a local peak at 2.5% after 4 months, then decreases to zero but strongly increases again until reaching 5.0% after 18 months. Finally, over the forecasting horizon, energy reaches its maximum pass-through after 4 months, at 2.0%.

Figure 9: Estimated Effect, Decomposition by Category

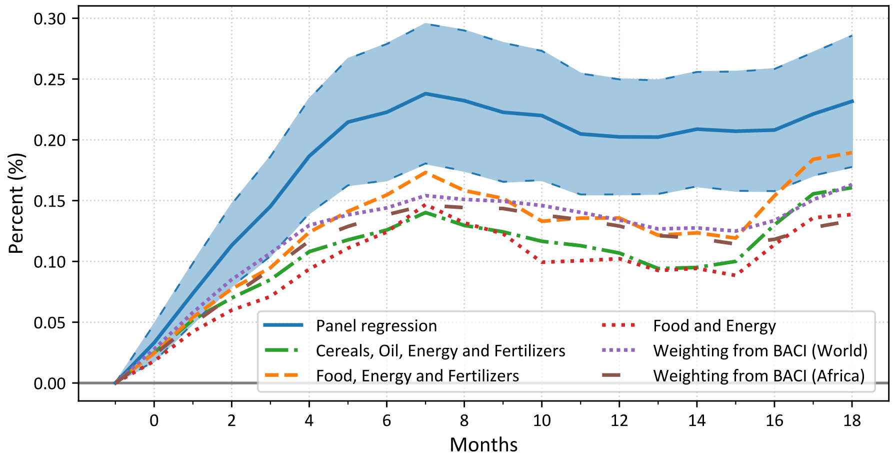


Note: Impulse response of total CPI to a simultaneous 1% shock on the prices of 17 commodities in 48 African countries, estimated between 2002m02 and 2021m04, with a weight corresponding to real GDP at purchasing power parity as of 2021. The blue curve corresponds to the results of a panel regression, the blue area corresponds to the 95% confidence interval of this regression. The stacked bars correspond to the impulse response of total CPI to each shock on the 17 commodities, grouped by category. Cereals include maize, wheat, rice, soybeans and groundnut. Vegetable oils include sunflower oil, palm oil and rapeseed oil. Energy includes crude oil, natural gas and coal. Fertilizers include DAP, TSP, potash, urea and phosphate rock. Other commodity corresponds to sugar.

How do these results compare to specifications closer to the existing literature? To answer this question, we compare our baseline cumulated response to cumulated responses for three alternative specifications. To do so, we first estimate the price response to shocks on several aggregate indices published by the World Bank. First, we plot the response of consumer prices to aggregate food and energy commodity prices. This specification is therefore close to Gelos and Ustyugova (2017). Second, we add to these two aggregate indices the aggregate index of fertilizers prices. In a third specification, we control for both the aggregate indices of energy and fertilizers, and add to them the aggregate indices of cereals and vegetable oils prices. However, the aggregate indices published by the World Bank do not reflect fully the set of commodities we focus on. Indeed, the aggregate index for cereals includes rice, wheat, maize and barley (while we do not include the latter). Similarly, the index for vegetable oils includes coconut oil and three different types of soybeans products (soybeans, soybeans oil and soybeans meals), but not sunflower oil. Importantly, the food index published by the

World Bank includes meat, fruits and beverages, which we do not focus on. Therefore, in order to rule out the possibility that the different results reflect only a difference in the set of commodities we consider, we reconstruct a set of aggregated prices for energy, fertilizers, cereals and vegetable oils based on the BACI dataset for 2020. To do so, we compute, for each of the 17 commodities we consider, its global traded value in 2020. We then compute its weight in the category it belongs to as the ratio between its global traded value and the sum of global traded values of all commodities belonging to the category. We then aggregate, for each category, the commodity-wise prices using the computed weights. The aggregated prices for each category therefore contain only the commodities we focus on in our baseline analysis, with weights representative of global trade as of 2020. Finally, using the same BACI data, we compute an additional set of aggregate index based on the structure of African imports: the weights are derived from the share of each commodity in the total imports of the category it belongs to in Africa. Such a set of aggregate indices allows to test whether an index reflecting more closely the import structure of the African continent yields a higher pass-through[6].

Figure 10: Comparison of Baseline Effect with Alternative Specifications



Note: Impulse response of total CPI to a simultaneous 1% shock on the prices of 17 commodities in 48 African countries, estimated between 2002m02 and 2021m04, with a weight corresponding to real GDP at purchasing power parity as of 2021. The blue curve corresponds to the results of the panel regression that includes the 17 commodities, the blue area corresponds to the 95% confidence interval of this regression. Each other curve corresponds to a regression which includes the prices of different commodity groups.

Theoretically, as discussed previously, two concurrent effects could affect the relative pass-through of disaggregated or aggregated commodities. On the one hand,

[6]Building composite indices based on the weight of each of the 17 commodities in Africa's consumption would have been relevant, but this is hardly feasible given available data.

as hypothesized above, given that aggregated commodities are based on a weighting scheme unrepresentative of local consumption shares, it is likely that it creates a measurement error, and therefore entails a lower pass-through. On the other hand, including separately commodities in the regressions might cause an underestimation of the pass-through, because of substitution effects: if the price of a single good rises while those of close substitutes don't, substitution might be easy to implement, thus causing weaker inflationary effects (because of a lower demand for the good whose prices increased). To the contrary, if several substituable goods see their price increase at the same time, substitution might be less easy to implement, and inflationary might be higher. Therefore, identifying separately the effects of commodity prices could lead to an underestimation of the pass-through. [7]

For these five specifications, we find cumulated responses that reach a plateau ranging between 10% and 15% and are systematically below the confidence intervals of our baseline specification. These results are reported in Figure 10. The estimates are very much in line with the estimates in the existing literature, and notably those in Bekkers et al. (2017) and Gelos and Ustyugova (2017). All these results show that disaggregating commodity prices data in order to capture their heterogeneity, to control for their cross-correlation and to be agnostic about the weight of each commodity yields a higher pass-through than specifications that include only aggregated indices. The potential downward bias in the commodity-by-commodity estimation due to an imperfect capture of substitution does not seem to play an important role. Finally, results obtained using weights representative of African import structures are not substantially different from the others. This result, which reinforces the need to use disaggregated commodity indices, might reflect the fact that structure of African imports is a very imperfect proxy for the structure of consumption.

4.2 Additional Results and Robustness

In this section, we provide several alternative results as well as robustness tests in order to refine the interpretation of our results.

First, we test the hypothesis of asymmetric reactions of prices between positive and negative shocks. To do so, we run our baseline panel regression, interacting the shocks on each commodity with a dummy indicating whether the shocks is positive or negative:

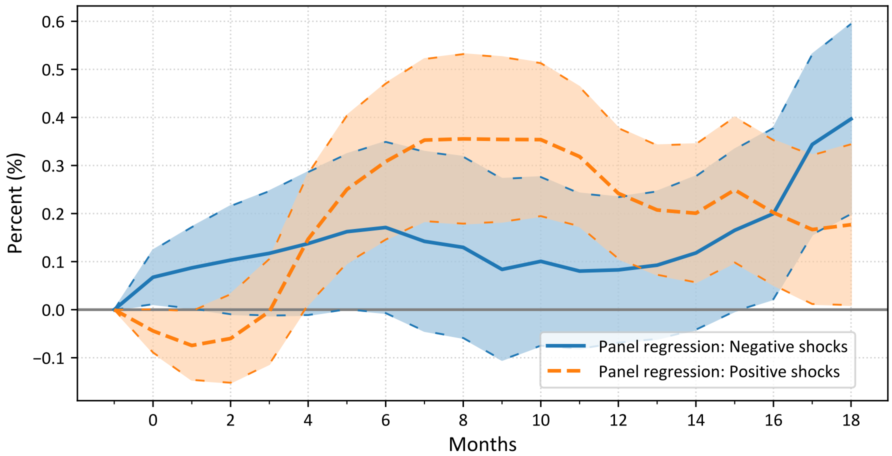
[7] Another related issue is how the choice of modelling interacts with the chaining of the consumer price indices, which, to the extent that it is implemented, takes into account substitution effects and thus affects CPI measures. However, because chaining is generally implemented at a low frequency basis (typically every year in the best cases), this is unlikely to play a role in the comparison we run, since out analysis is done at a monthly level and the effects take less than a year to materialize.

$$g_{CPI,i,m-1;m+h} = \sum_{k \in K} \theta_k^h \, g_{P_{k,m-1;m}} + \sum_{k \in K} \beta_k^h \, g_{P_{k,m}} \times \mathbb{1}_{g_{P_{k,m}}>0} + \gamma^h \, \mathbf{X}'_{i,m} + \mathbf{FE}_{i,m} + \varepsilon_{i,m}^h \quad (3)$$

where $\mathbb{1}_{g_{P_{k,m-1;m}}>0}$ is a dummy equal to one when the global commodity price shock is positive and zero otherwise.

The vector $\mathbf{X}_{i,m} = \left\{ \Delta log(e_{USD,i,m-1;m}),\ CRND\ intensity_{i,m},\ Conflict_{i,m},\ \Delta log(i_{MPR,i,m-1;m}) \right\}$ comprises all the control variables included in Equation (1) and the vector $\mathbf{FE}_{i,cm,t} = \left\{ \delta_i^h,\ \delta_{cm}^h,\ \delta_t^h,\ \delta_{i,cm}^h,\ \delta_{i,t}^h \right\}$ comprises all the fixed effects included in Equation (1).

Figure 11: Asymmetric Responses

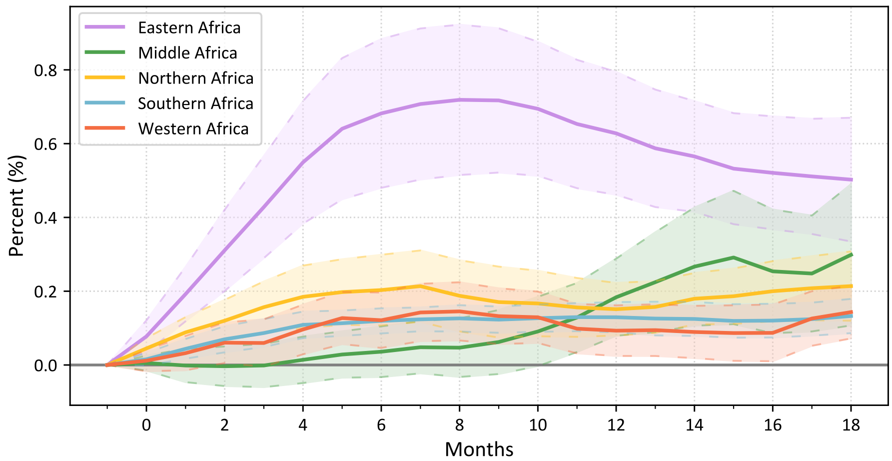


Note: Impulse responses of total CPI to a simultaneous 1% shock on the prices of 17 commodities in 48 African countries, estimated between 2002m02 and 2021m04, with a weight corresponding to real GDP at purchasing power parity as of 2021. The orange dashed curve correspond to the baseline panel specification when global commodity prices shocks are positive, the blue plain curve corresponds to the baseline panel specification when global commodity prices shocks are negative, the shaded areas correspond to the 95% confidence intervals of the respective regressions.

The results are presented in Figure 11. Overall, we find positive and significant reactions for both negative and positive shocks, but with different magnitudes and shapes of cumulative price response. Positive commodity price shocks have a muted reaction during the three first months, but then react very strongly, with a pass-through reaching about 36% after 8 months, which then progressively decreases. As regards negative shocks, they entail a progressive pass-through, which increases immediately after the shock until reaching 17% after six months. It then decreases progressively, before gaining momentum again after about 15 months, until reaching 40%. The differences between the two pass-through are statistically significant in the first 2 months, between months 7 to 11, and after month 17. These results therefore evidence that, during the first year after a shock, positive prices react more strongly but with a delay, suggesting that retailers might delay the moment to pass-through during the first months following the shock. This might potentially reflect diverse motives such as altruistic behaviours, which have been documented in some studies (see for example Gagnon and López-Salido, 2020, for the case study of snow storms in the US), competition effects or reputational motives. This could also reflect the existence of price caps and subsidies, which might help delaying the price response to positive shocks.

In the outer range of the projection horizon, negative shocks tend to be transmitted more strongly, suggesting stronger second-round effect. In order to interpret correctly this results, it is worth reminding that Africa is overall characterized by a high inflation environment. Therefore, the pass-through of negative shocks to prices need not entail a decrease in consumer prices (which would be unrepresentative of the inflation regimes observed in Africa), but a lower increase of prices compared to those that would have been observed absent the shock. In this context of high inflation, the second-round effects of a positive shock might be more short-lived (as it represents one among many other factors contributing to high inflation), compared to the moderating effects of negative shocks, which might contribute more durably to slowing down prices.

Figure 12: Results by African Regions

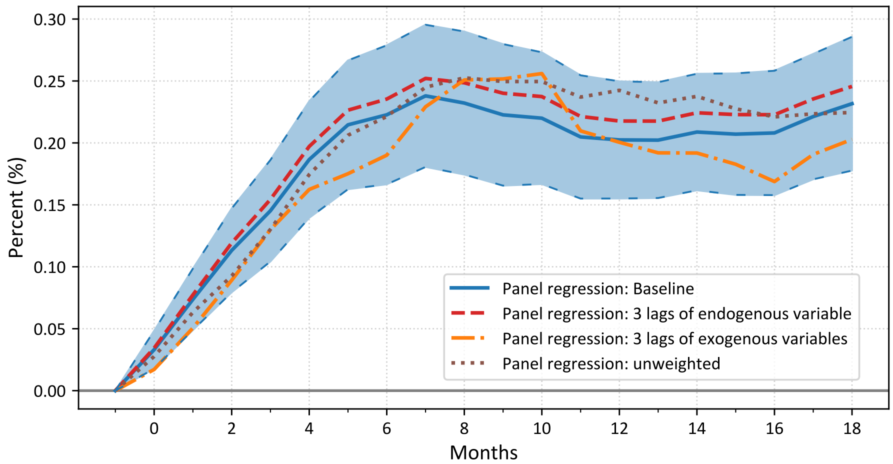


Note: Impulse response of total CPI to a simultaneous 1% shock on the prices of 17 commodities in 48 African countries, estimated between 2002m02 and 2021m04, with a weight corresponding to real GDP at purchasing power parity as of 2021. Each curve corresponds to the baseline results for a specific African region, following the definition of the United Nations. The shaded areas correspond to the 95% confidence intervals of their respective regression.

A second additional result concerns the regional heterogeneity of pass-through in Africa. In Figure 12, we plot the results of the baseline panel regression, where the shocks are interacted with a dummy for each African region (according to the definition given by the UN, depicted in Appendix Figure A.1). Eastern Africa stands out as the region with the highest pass-through, because of the strong reaction of prices in Ethiopia (which we document in Section 5). In other regions, the pass-through are more homogeneous, but all significant at least once at the 5% over the projection horizon.

Finally, we also document the reaction of consumer prices to the main covariates included in the baseline specification. The main results are documented in Appendix Table B.3. The covariate with the most striking effect is the local currency-USD exchange rate: after a 1% depreciation of the local currency, we find a significant increase of consumer prices, with a pass-through reaching a maximum of 8.5% after 3 months, which is short-lived and decreases to zero after about a year. This pass-through is significantly lower than other estimated exchange rates pass-through. For instance, Razafimahefa (2012) finds an exchange rate pass-through of about 40% in Sub-Saharan Africa. However, this result is obtained without controlling for the prices of commodities. The fact that the exchange rate pass-through is much lower when controlling for commodity prices suggests that a substantial share of the exchange rate pass-through in Africa might be channelled through increased commodity prices in local currencies, which are eventually transmitted to consumer prices. The variables indicating the intensity of civil conflict and climate-related natural disaster also have a positive effect on prices, even though to a much lesser extent. The maximum observed significance of both variables is of 10%, after 4 months for climate-related natural disaster intensity and after 3 months for civil conflicts intensity. Finally, conditionally on all these variables, the monetary policy interest rates do not appear to significantly affect consumer prices, suggesting an overall limited transmission of monetary policy in our sample.

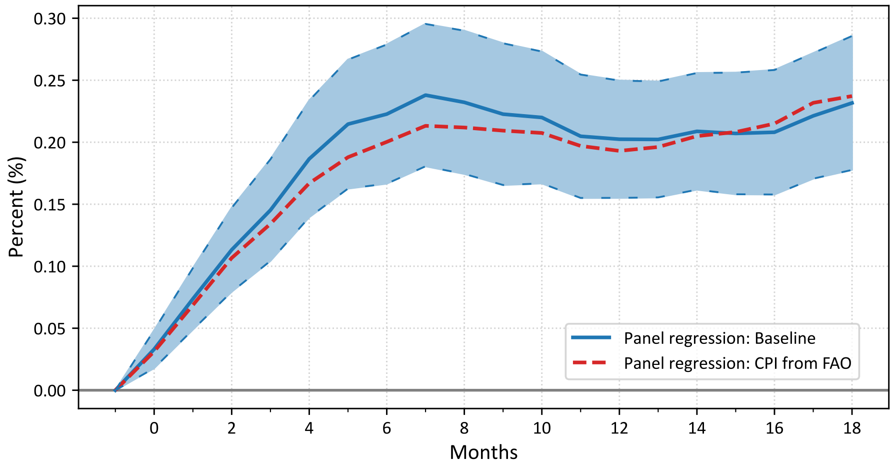
Figure 13: Robustness Checks: Alternative Specifications



Note: Impulse response of total CPI to a simultaneous 1% shock on the prices of 17 commodities in 48 African countries, estimated between 2002m02 and 2021m04, with a weight corresponding to real GDP at purchasing power parity as of 2021. The blue curve corresponds to the baseline results of a panel regression, the blue area corresponds to the 95% confidence interval of this regression, the red dashed line corresponds to an alternative specification of Equation (1) which comprises 3 lags of the endogenous variable, the orange dashed-dotted line corresponds to a specification of Equation (1) which comprises 3 lags of the exogenous variables, and the brown dotted line corresponds to the estimates from of Equation (1) when countries are unweighted.

We also test the robustness of our baseline panel regression to alternative specifications. In Figure 13, we compare our baseline specification with a specification adding three lags of the endogenous variable (dashed red line), 3 lags of the commodity prices (dashed orange line), and with an unweighted specification. All of the estimated alternative specifications lie within the 95% confidence interval band of the baseline panel specification.

Figure 14: Robustness Checks: Alternative Source for the Consumer Price Index



Note: Impulse response of total CPI to a simultaneous 1% shock on the prices of 17 commodities in 48 African countries, estimated between 2002m02 and 2021m04, with a weight corresponding to real GDP at purchasing power parity as of 2021. The blue curve corresponds to the baseline results of a panel regression, the blue area corresponds to the 95% confidence interval of this regression, and the red dashed line corresponds to the baseline specification using CPI data from FAO.

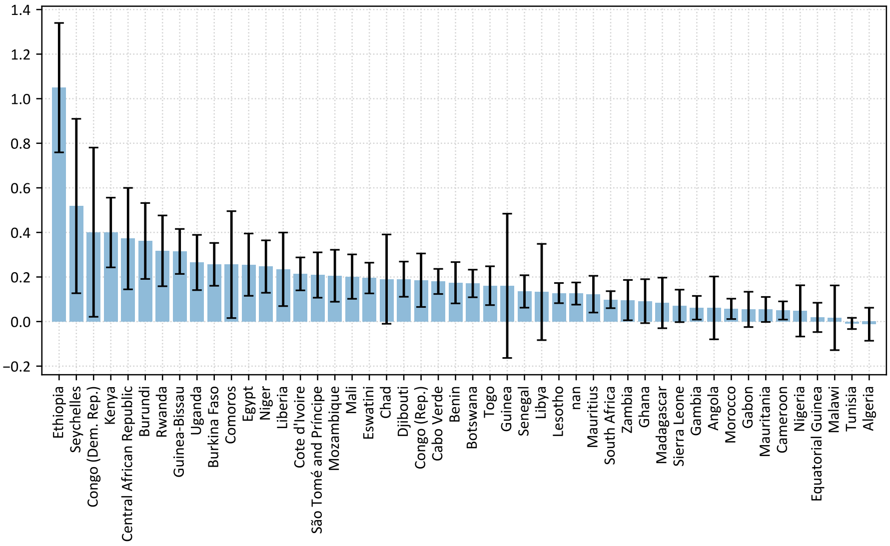
Finally, in Figure 14, we check that our results are robust to using alternative sources of data for the variable of interest (i.e. CPI). We compare our baseline panel specification to a specification in which we use the FAO price indices rather than data from the World Bank: the cumulative price responses are very close and within the confidence interval, with slightly lower values in the specification using data from the FAO.

5 Country-Specific Results and Transmission Channels

In this section, we present results for the country-by-country specification, which are useful to explore the role of country-specific characteristics (and notably of country-specific consumption structure) in shaping the pass-through. Figure 15 summarizes our findings for the mean pass-through over 18 months (the full cumulative responses with confidence intervals are shown in Appendix Figures B.1 and B.2, and the contributions of the different commodities are shown in Appendix Figures B.3 and B.4).

Using the average over the projection horizon rather than a measure of the long-run pass-through is interesting in our case, as this gives information not only about the level of the price reaction but also about its pace.

Figure 15: Mean estimated effect over 18 months



This figure plots the average cumulated response over 18 months for each country, with a 95% confidence interval.

We find an important heterogeneity across the 48 countries in our sample. The av-erage observed effects over a year and a half range from non-significant negative values in only two countries (Tanzania and Algeria) to 100% in Ethiopia. In the 45 remaining countries with positive average pass-through, the highest observation is for Seychelles (52%), and 33 countries have average pass-through over a year that are statistically significant at the 5% level. Finally, and reassuringly, aggregating the cumulated response over countries yields an aggregate impulse response for Africa (represented by the red curve in Figure 7) that is very close to the one obtained using the panel data estimation.

In order to study the determinants of this heterogeneity across countries, we run two separate series of exercises. First, in Table 2, we relate the average pass-through over 18 months to the average GDP per capita, the share of food in the consumption basket given by the Global Consumption Database, the road mean speed score, which proxies transportation infrastructure quality, to a dummy indicating whether the country is net oil importer or exporter, to the value of energy subsidies, to the share of taxes on goods and services in government revenues, to trade openness and an index of government efficiency. We find that GDP per capita, the road mean speed score, being net oil exporter and the presence of energy subsidies are all associated with a lower pass-through and that this relation is statistically significant at the 5% level. The share of food and energy in the consumption basket and the share of taxes on goods and services in government revenues are both positively associated with the pass-through, at a statistical significance level of 10%, suggesting that consumption structure and the composition of fiscal policy might matter when estimating the pass-through. Openness to trade and government efficiency do not seem to be associated with the value of the mean pass-through. Importantly, as shown in Appendix Table B.4, these relations are robust to excluding Ethiopia, whose average pass-through is particularly high compared to other countries.

Table 2: Regressions of pass-through on observed characteristics of the country

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Pass-Through:	Total	Total	Total	Total	Total	Total	Total	Total
Log GDP per cap. PPP	-0.057							
	(2.07)**							
Log share of food & energy		0.123						
		(1.92)*						
Road mean speed score			-0.004					
			(2.39)**					
Net oil exporter				-0.140				
				(3.71)***				
Log energy subsidy					-0.022			
					(2.18)**			
Log taxes to GDP						0.070		
						(1.87)*		
Log openness to trade							-0.061	
							(1.18)	
Government efficiency								-0.008
								(0.22)
Constant	0.652	-0.291	0.430	0.214	0.196	-0.034	0.431	0.185
	(2.83)***	(1.25)	(3.49)***	(7.58)***	(8.05)***	(0.30)	(2.04)**	(4.61)***
R^2	0.10	0.05	0.07	0.09	0.05	0.03	0.04	0.00
N	48	38	41	48	48	31	48	48

T-Stat in parentheses. Robust standard errors. * Significant at the 10 percent level, ** Significant at the 5 percent level, ** Significant at the 1 percent level.

We further explore the relation between the share of food and energy in the consumption basket and the value of the pass-through in Table 3. Column (1) repeats the results presented in Table 2 column (2) for comparison purposes. As shown in Table 3 columns (2) to (4), the positive, weakly significant association between the mean total pass-through and the share of food and energy in the consumption basket is confirmed when using data from the African Development Bank, which covers the entire sample. Finally, when distinguishing between the consumption structure of rural and urban households, we still find positive effects, but slightly smaller (which might suggest a lower precision of the estimation of the consumer basket structure) and not statistically significantly different from each other.

Table 3: Regressions of pass-through on different measures of food consumption

	(1)	(2)	(3)	(4)
Pass-Through:	Total	Total	Total	Total
Log share food & energy (WB - All)	0.123			
	(1.92)*			
Log share food & energy (AfDB)		0.158		
		(1.78)*		
Log share food & energy (WB - Rural)			0.111	
			(1.59)	
Log share food & energy (WB - Urban)				0.072
				(1.74)*
Constant	-0.291	-1.171	0.249	0.251
	(1.25)	(1.54)	(4.40)***	(4.41)***
R^2	0.05	0.03	0.02	0.02
N	38	46	38	38

T-Stat in parentheses. Robust standard errors. * Significant at the 10 percent level, ** Significant at the 5 percent level, ** Significant at the 1 percent level.

Finally, we show in Appendix Table B.5 that evidence on a relation between total pass-through and the exchange rate regime and monetary policy framework appears to be weak. Results reported in column (4) indicate that central bank independence seems to be associated with a lower pass-through, especially in the case of a floating exchange rate. However, the estimates are statistically significant at the 10% level only.

In a second exercise, we relate the pass-through of different commodities to the share of several related items in the consumption basket according to the Global Consumption Database. Namely, we match the pass-through of rice with the share of rice, the pass-through of sugar with the share of sugar, the pass-through of wheat with the share of bread, pasta and pastry, the pass-through of vegetable oils with the share of fats excluding butter, the pass-through of coal with the share of energy excluding fuel and electricity, the pass-through of crude oil to the pass-through of energy for personal transportation, and the pass-through of natural gas to the share of gas.

The main challenge in this exercise lies in the fact that, within each category, there exists strong variations in consumption shares and pass-through, which gives rise to possible outliers. To tackle this challenge systematically, we exclude from the analysis all estimated pass-through and shares in consumption baskets which are more than 3 standard deviation above or below the median for each of these two variables. This amounts to dropping 4% of the sample.

Table 4: Regressions of pass-through by component on their share in the basket

	(1)	(2)	(3)	(4)
Share of component	0.412	0.438	0.154	0.109
	(3.89)***	(4.20)***	(1.32)	(0.99)
Constant	0.010	0.009	0.015	0.054
	(3.39)***	(2.97)***	(4.92)***	(5.70)***
R^2	0.05	0.22	0.21	0.40
Observations	255	255	255	255
Country FE	N	Y	N	Y
Commodity FE	N	N	Y	Y

T-Stat in parentheses. Robust standard errors. * Significant at the 10 percent level, ** Significant at the 5 percent level, ** Significant at the 1 percent level.

In Table 4, we provide estimates without any fixed effect (column 1), with country fixed effect (column 2) component fixed effect (column 3), and both country and component fixed effects (column 4). In the specification without any fixed effect (column 1), we find a positive correlation between components pass-through and their weight in the consumption basket, with a coefficient of 0.412. This positive correlation is still observed (with a coefficient of 0.438) when country fixed effects are included in the regression (column 2), and the R^2 increases substantially (from 5% to 22%). This indicates that, on average across all commodities, some countries on average have higher pass-through irrespective of the weights of commodities, but that within a given a country, commodities with higher shares in the consumption basket tend to have a higher pass-through. When we include commodity fixed effects (column 3), the R^2 is also much higher than in column (1) (21%) but the coefficient of the share of consumption becomes much smaller (0.154) and statistically not-significant. This indicates that, on average across countries, some commodities have on average higher pass-through and that they also tend to represent higher shares in the consumption basket. This typically captures differential effects between food and energy commodities, the former having both higher weights and higher pass-through on average (see Figure B.5 in Appendix for a graphic representation). However, in this context, as the coefficient of the share in consumption basket becomes small and non-significant, this indicates that for a given commodity, its pass-through is not necessarily higher in countries in which its weight is higher. Finally, when both country and commodity fixed effects are included, the R^2 further increases to 40%, and the coefficient of the share of commodity further decreases 0.109 and remains statistically not-significant.

Overall, such results therefore highlight that the correlation between the pass-through of commodities and their share in consumption is driven by within-country variations, but that unobserved heterogeneity across countries and types of commodities both play an important role in explaining the pass-through of global commodity prices to consumer prices.

6 Conclusion

In this paper, we showed that global commodity prices significantly pass-through to consumer prices in Africa. Using data for the period 2002m02–2021m04, and focusing on 17 commodities among energy, cereals, sugar, vegetable oils and fertilizers, we find a maximum pass-through of 24%, and a long-run pass-through of about 20%, which is significantly higher than existing results in the literature.

We argue that this stronger pass-through reflects the fact that we take into account the heterogeneity of commodity prices, as we control for each of them separately, and the fact that we are agnostic about the weight of each commodity in the consumptio basket. Using a country-by-country approach, we also document a strong heterogeneity of pass-through, which mostly reflects differences in GDP per capita, the share of food and energy in the consumption basket, the status of being a net oil importer or exporter, and policy decisions such as the implementation of energy subsidies. This country-by-country approach enables us to relate the pass-through of various commodities to share of related products in the consumer basket. Doing so, we find that the share of commodities in the consumer basket is significantly correlated with the estimated pass-through, and that this correlation is driven by within-country variation: for a given country, commodities with a stronger weight in the consumption basket also have a stronger pass-through. However, our results also highlight a strong effect of unobserved country and commodity heterogeneity on global commodity pass-through. Exploring the determinants of the latter would represent an interesting pathway for future research.

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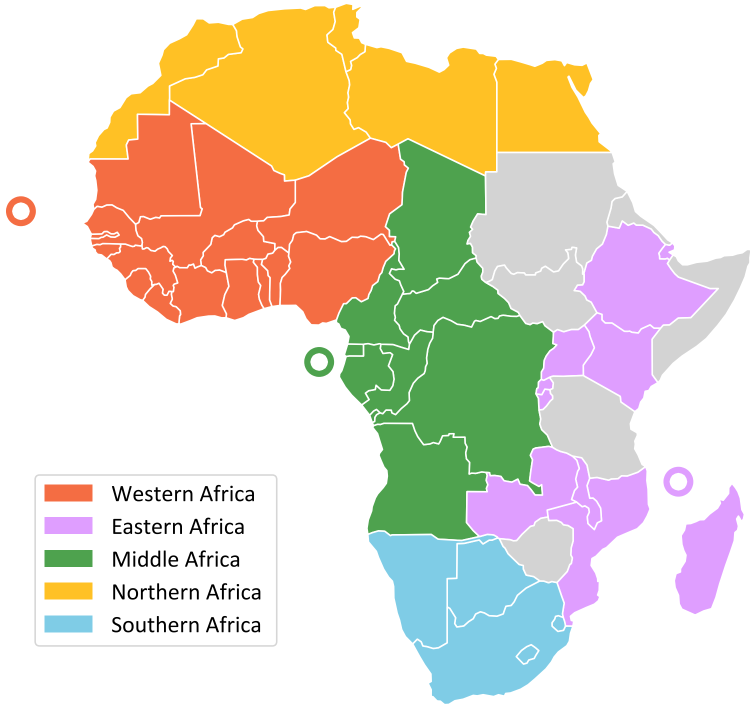
Appendix

A Country List and Data Sources

Table A.1: List of Countries

Country	Share of GDP in Africa (%) - 2021	Country	Share of GDP in Africa (%) - 2021
Algeria	7.89	Kenya	3.99
Angola	3.2	Lesotho	0.09
Benin	0.69	Liberia	0.12
Botswana	0.61	Libya	1.34
Burkina Faso	0.78	Madagascar	0.68
Burundi	0.14	Malawi	0.48
Cabo Verde	0.06	Mali	0.76
Cameroon	1.56	Mauritania	0.4
Central African Republic	0.07	Mauritius	0.42
Chad	0.41	Morocco	4.49
Comoros	0.04	Mozambique	0.64
Congo (Dem. Rep.)	1.65	Namibia	0.37
Congo (Rep.)	0.31	Niger	0.5
Côte d'Ivoire	2.35	Nigeria	16.9
Djibouti	0.09	Rwanda	0.46
Egypt	20.46	São Tomé and Principe	0.01
Equatorial Guinea	0.4	Senegal	0.94
Eswatini	0.16	Seychelles	0.04
Ethiopia	4.43	Sierra Leone	0.22
Gabon	0.52	South Africa	12.78
Gambia	0.09	Togo	0.3
Ghana	2.87	Tunisia	1.91
Guinea	0.6	Uganda	1.72
Guinea-Bissau	0.07	Zambia	0.98

Figure A.1: African Regions



Source: United Nations, elaboration by the authors. Countries in grey are not included in our sample.

Table A.2: Data Sources

Variable:	Source:
Consumer price index	Ha et al. (2021)
Commodity prices	World Bank (Pink Sheet) - April 2022
2021 PPP real GDP	IMF (WEO)
Nominal exchange rate (LCU per USD)	IMF (IFS)
Monetary policy rates	IMF (IFS)
Climate-related natural disasters	EM-DAT dataset (CRED, 2022)
Violence and conflict	ACLED (Raleigh et al., 2010)
Population	United Nations (DESA-PD): World Population Prospects
Trade openness	IMF (DOTS)
Energy subsidy	Vernon et al. (2021)
Exchange rate and monetary policy regime	IMF (ARE-AER 2021)
Road mean speed score	Moszoro and Soto (2022)
Consumption basket structure	World Bank (Global Consumption Database)
Central Bank independence	Romelli (2022)
Taxes on goods and services	World Bank, based on IMF Government Finance Statistics
Net oil exporters	IMF classification
Share of food and/or energy in consumption basket	World Bank (Global Consumption Dataset)
	AfDB (2012)

Note: The monetary policy rate is proxied by the average between the deposit and lending rates.

B Additional Results

Table B.1: Panel data specification - Results by component

Commodity	(1) t=0	(2) t=3	(3) t=6	(4) t=9	(5) t=12	(6) t=15	(7) t=18
Total	0.033***	0.145***	0.223***	0.223***	0.202***	0.207***	0.232***
	(4.24)	(6.95)	(7.78)	(7.64)	(8.39)	(8.28)	(8.41)
Crude oil	0.005	0.012	0.012	-0.000	-0.006	-0.005	-0.016
	(1.69)*	(1.82)*	(1.31)	(0.02)	(0.61)	(0.36)	(1.04)
Coal (South Africa)	0.005	0.019	0.016	0.017	0.022	0.021	0.006
	(1.20)	(2.10)**	(1.42)	(1.52)	(2.10)**	(1.66)*	(0.41)
Natural Gas (Index)	-0.003	-0.016	-0.018	-0.011	-0.013	-0.004	-0.002
	(0.93)	(2.00)**	(2.04)**	(1.07)	(1.45)	(0.46)	(0.20)
Groundnut	0.001	0.023	0.052	0.047	0.053	0.059	0.054
	(0.31)	(2.32)**	(3.50)***	(2.98)***	(3.87)***	(4.35)***	(3.59)***
Palm Oil	-0.007	-0.017	-0.035	-0.046	-0.043	-0.011	0.020
	(1.46)	(1.33)	(2.05)**	(2.57)**	(2.69)***	(0.60)	(1.03)
Soybeans	0.000	0.015	-0.013	-0.015	-0.015	-0.003	0.039
	(0.01)	(1.22)	(0.80)	(0.99)	(1.14)	(0.19)	(2.48)**
Rapeseed Oil	0.014	0.031	0.056	0.069	0.054	0.025	-0.020
	(1.94)*	(1.82)*	(2.66)***	(3.10)***	(2.74)***	(1.04)	(0.88)
Sunflower Oil	0.007	0.022	0.047	0.061	0.078	0.054	0.032
	(1.11)	(1.55)	(2.27)**	(2.76)***	(4.13)***	(2.61)***	(1.42)
Maize	0.005	0.001	-0.010	-0.007	-0.017	-0.012	0.020
	(0.78)	(0.09)	(0.73)	(0.45)	(1.19)	(0.86)	(1.31)
Rice (Thai, 05)	0.003	0.033	0.056	0.051	0.040	0.031	0.046
	(0.59)	(3.16)***	(4.24)***	(4.06)***	(3.57)***	(2.67)***	(3.43)***
Wheat (US, HRW)	-0.001	0.008	0.026	0.021	0.024	0.012	0.005
	(0.22)	(0.89)	(2.04)**	(1.51)	(2.08)**	(1.02)	(0.37)
Sugar (world)	-0.000	-0.004	0.015	0.036	0.031	0.027	-0.002
	(0.08)	(0.51)	(1.38)	(3.28)***	(3.11)***	(2.51)**	(0.14)
Phosphate rock	-0.004	-0.008	-0.015	-0.010	-0.004	-0.009	-0.011
	(2.46)**	(1.46)	(2.50)**	(1.65)*	(0.72)	(1.66)*	(1.84)*
DAP	0.007	0.001	-0.006	-0.022	-0.033	-0.022	0.016
	(1.65)*	(0.07)	(0.49)	(1.64)	(2.95)***	(1.77)*	(1.14)
TSP	-0.002	0.003	0.020	0.010	0.012	0.030	0.028
	(0.40)	(0.32)	(1.26)	(0.62)	(0.82)	(1.97)**	(1.79)*
Urea	0.002	0.006	0.004	0.006	0.007	-0.002	-0.002
	(0.99)	(1.20)	(0.75)	(1.01)	(1.38)	(0.26)	(0.37)
Potash	0.003	0.015	0.017	0.015	0.012	0.016	0.020
	(1.26)	(2.76)***	(2.64)***	(2.54)**	(2.49)**	(3.06)***	(2.76)***
R^2	0.36	0.62	0.71	0.81	0.90	0.92	0.93
Observations	10,178	10,031	9,887	9,743	9,599	9,455	9,311

T-Stat in parentheses. Robust standard errors. * Significant at the 10 percent level, ** Significant at the 5 percent level, , *** Significant at the 1 percent level.

Table B.2: Panel data specification - Results by category

Commodity	(1) t=0	(2) t=3	(3) t=6	(4) t=9	(5) t=12	(6) t=15	(7) t=18
Total	0.033	0.145	0.223	0.223	0.202	0.207	0.232
	(4.24)***	(6.95)***	(7.78)***	(7.64)***	(8.39)***	(8.28)***	(8.41)***
Veg. Oils	0.014	0.036	0.067	0.084	0.089	0.068	0.032
	(1.82)*	(2.28)**	(2.99)***	(3.59)***	(4.41)***	(3.11)***	(1.35)
Energy	0.007	0.016	0.009	0.006	0.003	0.012	-0.013
	(1.45)	(1.40)	(0.65)	(0.36)	(0.20)	(0.70)	(-0.69)
Cereals	0.008	0.081	0.112	0.097	0.085	0.087	0.164
	(0.97)	(4.22)***	(4.50)***	(3.83)***	(3.75)***	(3.58)***	(6.19)***
Fertilizers	0.005	0.017	0.020	0.000	-0.006	0.014	0.050
	(0.90)	(1.32)	(1.22)	(0.01)	(-0.38)	(0.90)	(2.99)***
Other (sugar)	0.000	-0.004	0.015	0.036	0.031	0.027	-0.002
	(-0.08)	(-0.51)	(1.38)	(3.28)***	(3.11)***	(2.51)**	(-0.14)

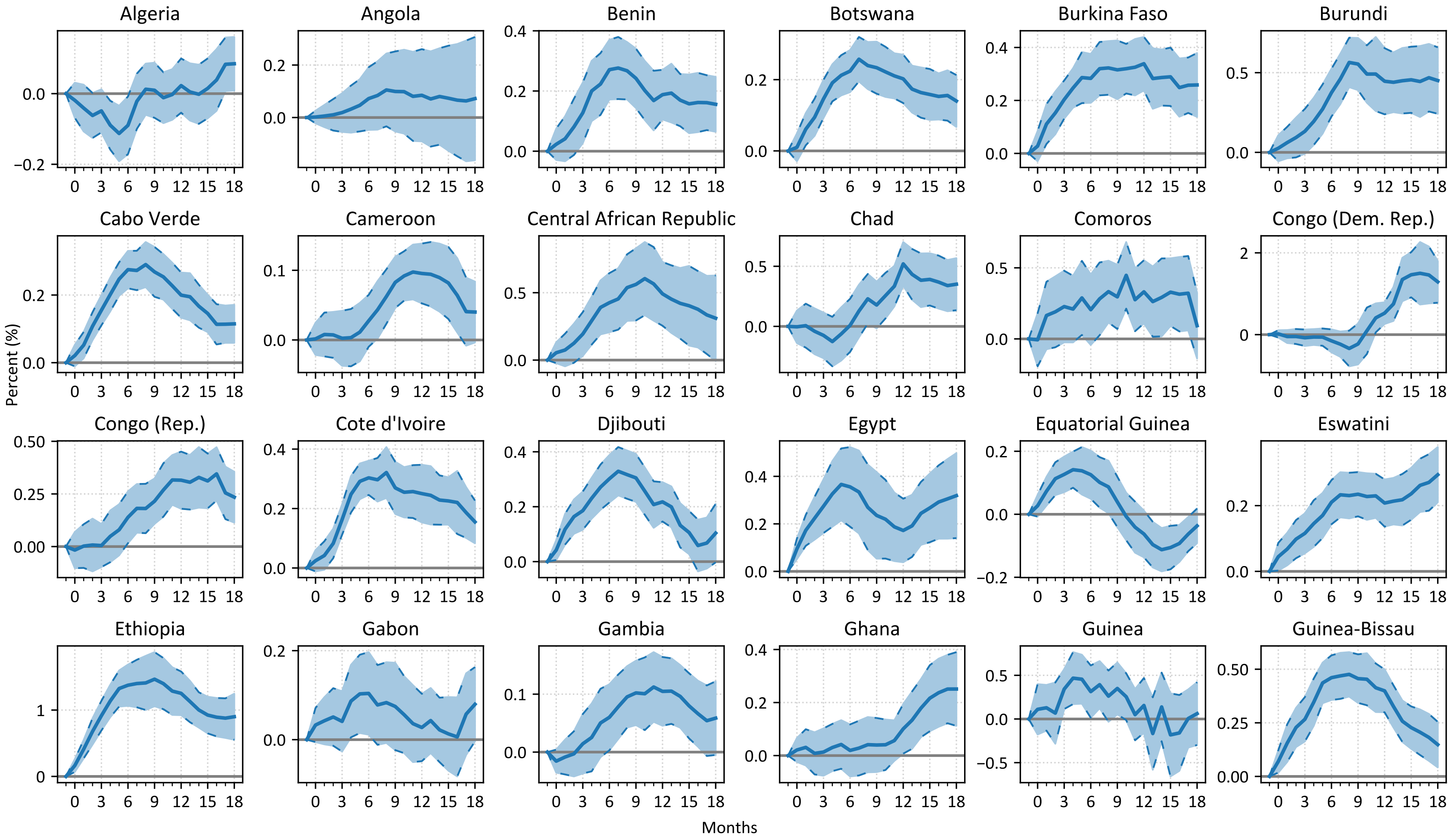
T-Stat in parentheses. Robust standard errors. * Significant at the 10 percent level, ** Significant at the 5 percent level, *** Significant at the 1 percent level.

Table B.3: Panel data specification - Results for covariates

Commodity	(1) t=0	(2) t=3	(3) t=6	(4) t=9	(5) t=12	(6) t=15	(7) t=18
USD/LCU	0.035576	0.085486	0.059867	0.054870	0.029227	-0.003016	-0.008212
	(2.44)**	(2.58)***	(1.66)*	(1.81)*	(1.60)	(0.12)	(0.25)
Victims of natural disasters	-0.000240	0.000736	0.000560	0.000147	-0.000235	0.000653	0.000587
	(1.04)	(1.50)	(1.04)	(0.26)	(0.42)	(1.10)	(1.04)
Victims of civil conflicts	0.000179	0.000525	0.000517	-0.000027	0.000665	0.000793	0.000877
	(0.93)	(1.85)*	(1.32)	(0.06)	(1.69)*	(1.35)	(1.27)
Interest rates	0.002509	0.003460	0.001107	-0.003908	-0.003459	0.000163	0.010136
	(1.18)	(0.75)	(0.16)	(0.47)	(0.49)	(0.02)	(0.55)
R^2	0.36	0.62	0.71	0.81	0.90	0.92	0.93
N	10,178	10,031	9,887	9,743	9,599	9,455	9,311

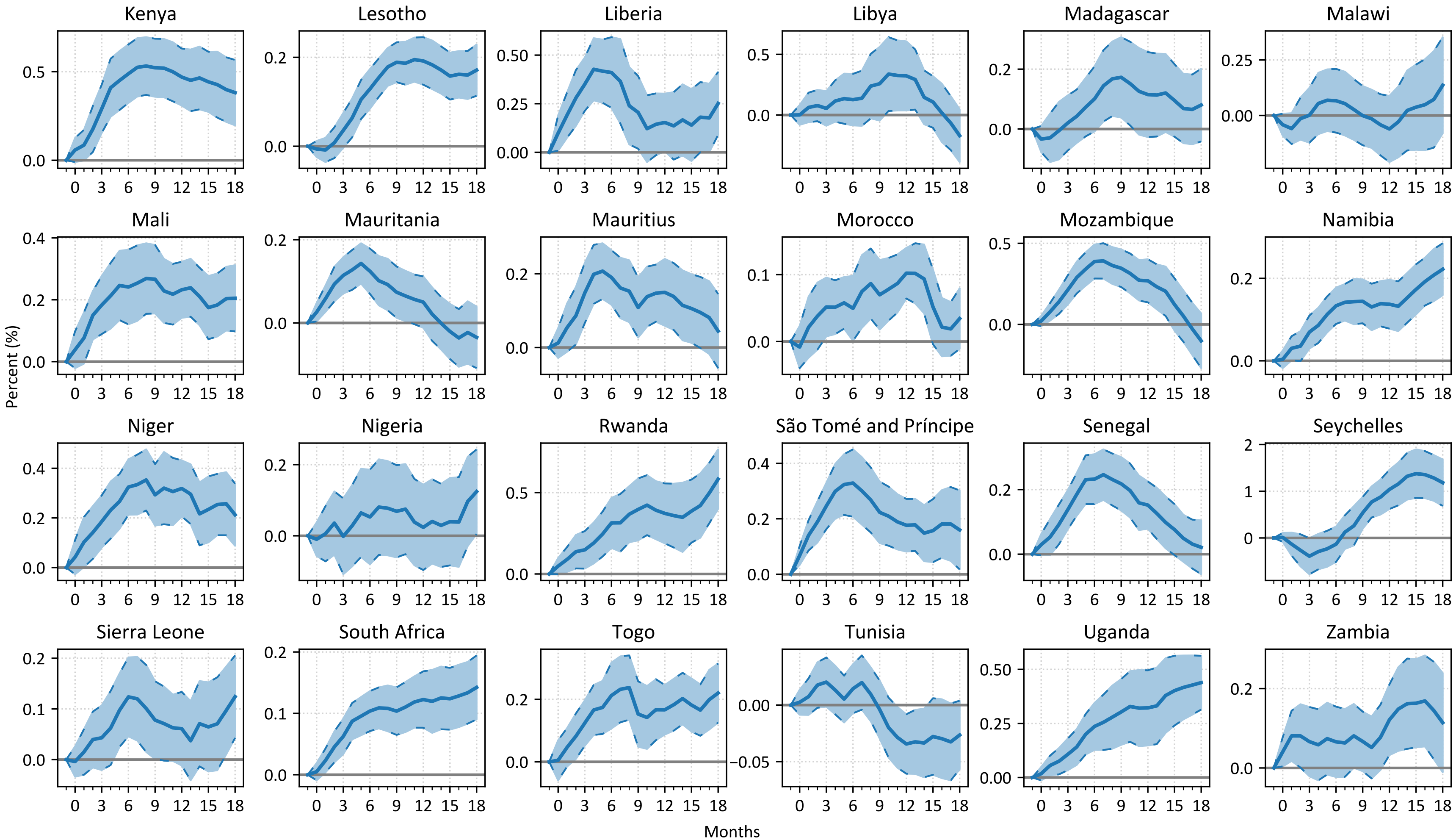
T-Stat in parentheses. Robust standard errors. * Significant at the 10 percent level, ** Significant at the 5 percent level, , *** Significant at the 1 percent level.

Figure B.1: Estimated Effect by Country, Decomposition by Category of Product



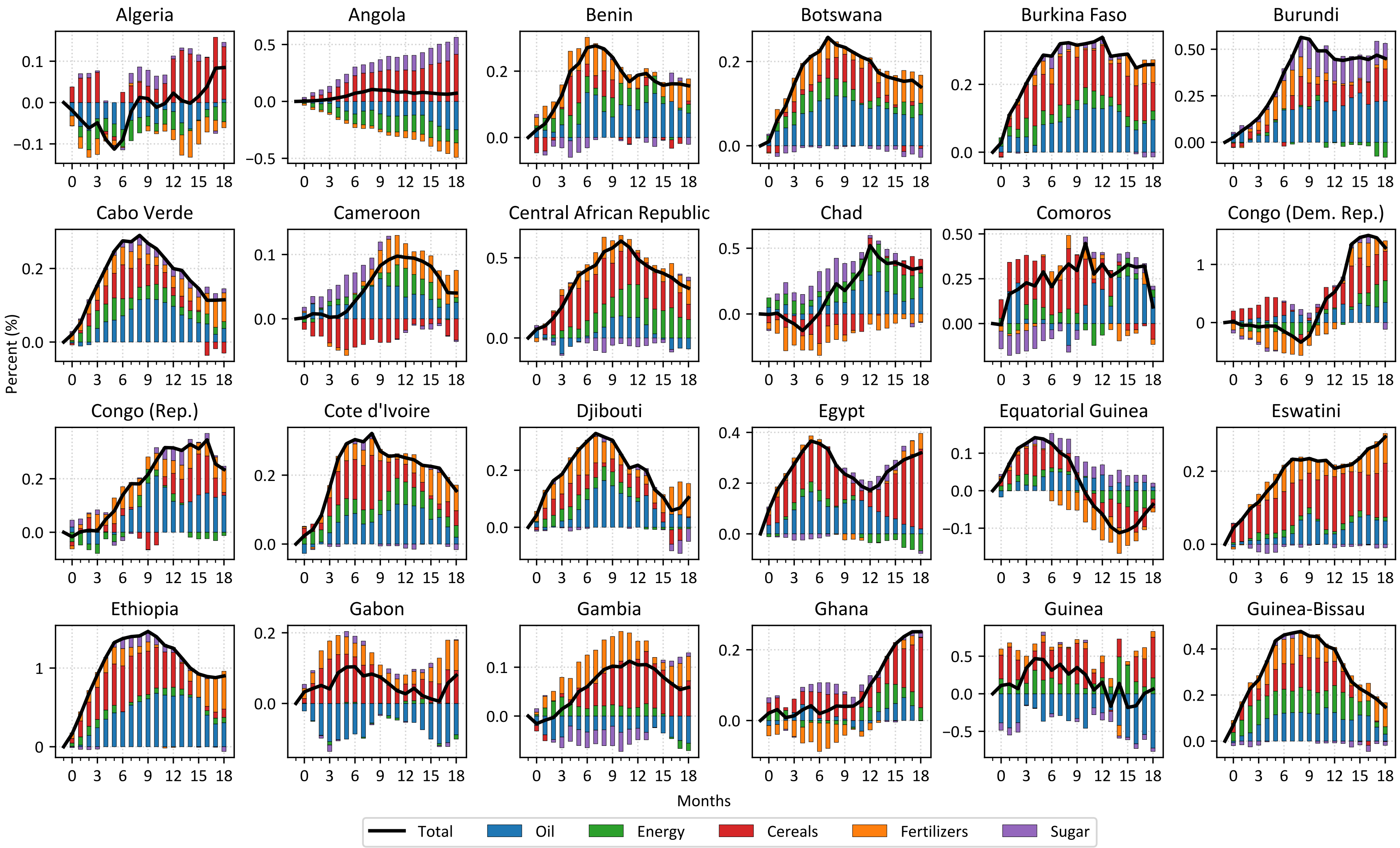
Note: Impulse response of total CPI to a simultaneous 1 % shock on the prices of 17 commodities at the country-level, estimated between 2002m02 and 2021m04. The blue curve corresponds to results country-wise regression, the blue area corresponds to the 95 % confidence interval of this regression.

Figure B.2: Estimated Effect by Country, Decomposition by Product



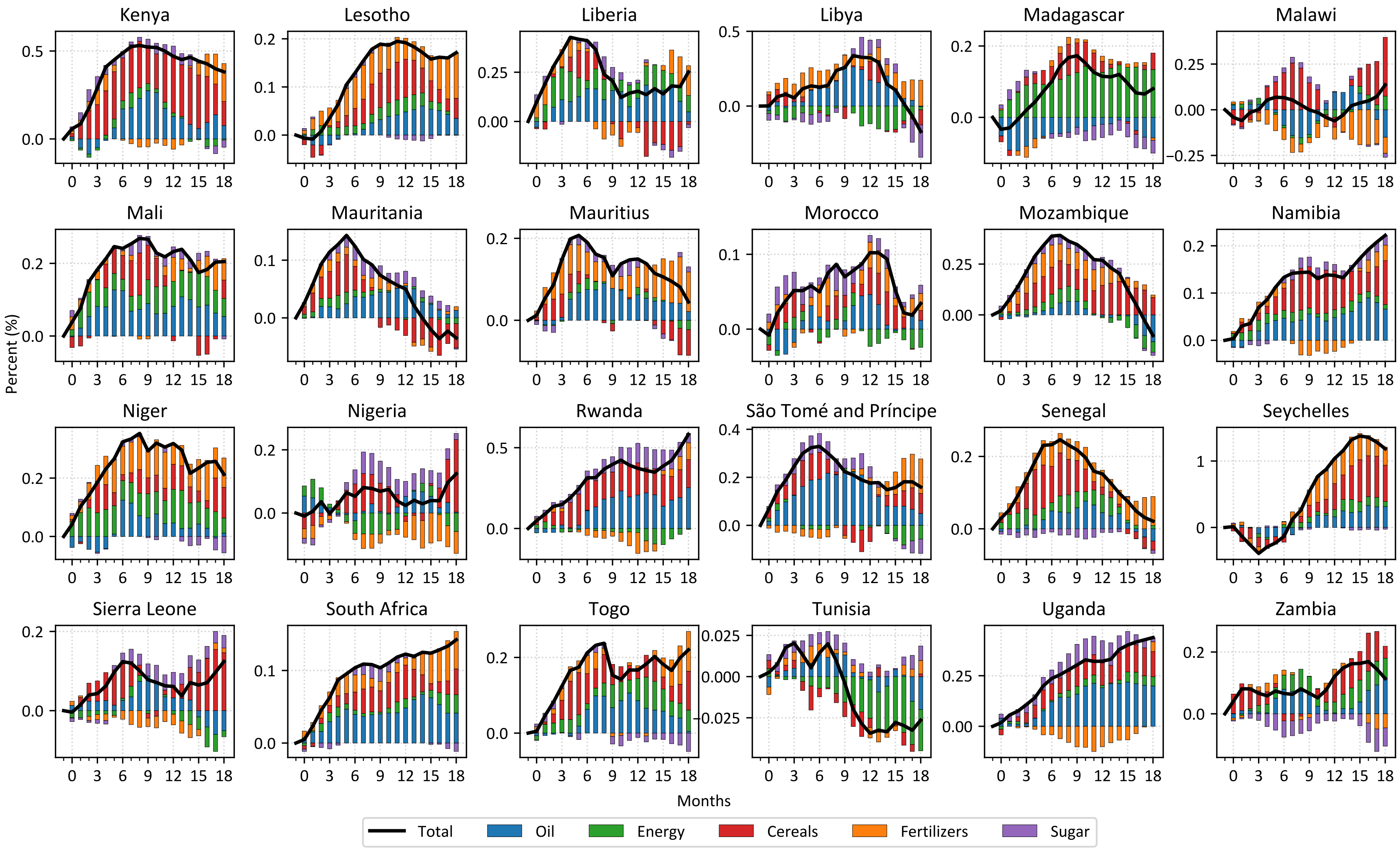
Note: Impulse response of total CPI to a simultaneous 1 % shock on the prices of 17 commodities at the country-level, estimated between 2002m02 and 2021m04. The blue curve corresponds to results country-wise regression, the blue area corresponds to the 95 % confidence interval of this regression.

Figure B.3: Estimated Effect by Country, Decomposition by Product



Note: Impulse response of total CPI to a simultaneous 1 % shock on the prices of 17 commodities at the country-level, estimated between 2002m02 and 2021m04. The blue curve corresponds to results country-wise regression, the blue area corresponds to the 95 % confidence interval of this regression. The stacked bars correspond to the impulse response of total CPI to each shock on the 17 commodities, grouped by category. Cereals include maize, wheat, rice, soybeans and groundnut. Vegetable oils include sunflower oil, palm oil and rapeseed oil. Energy includes crude oil, natural gas and coal. Fertilizers include DAP, TSP, potash, urea and phosphate rock. Other commodity corresponds to sugar.

Figure B.4: Estimated Effect by Country, Decomposition by Product



Note: Impulse response of total CPI to a simultaneous 1 % shock on the prices of 17 commodities at the country-level, estimated between 2002m02 and 2021m04. The blue curve corresponds to results country-wise regression, the blue area corresponds to the 95 % confidence interval of this regression. The stacked bars correspond to the impulse response of total CPI to each shock on the 17 commodities, grouped by category. Cereals include maize, wheat, rice, soybeans and groundnut. Vegetable oils include sunflower oil, palm oil and rapeseed oil. Energy includes crude oil, natural gas and coal. Fertilizers include DAP, TSP, potash, urea and phosphate rock. Other commodity corresponds to sugar.

Table B.4: Regressions of pass-through on observed characteristics of the country - without Ethiopia

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log GDP per cap. PPP	-0.040 (1.79)*							
Log share food & energy		0.075 (1.83)*						
Road mean speed score			-0.003 (2.33)**					
Net oil exporter				-0.118 (3.79)***				
Log energy subsidy					-0.024 (2.50)**			
Log taxes to GDP						0.061 (1.78)*		
Log openness to trade							-0.029 (0.71)	
Government efficiency								-0.014 (0.37)
Constant	0.496 (2.81)***	-0.124 (0.80)	0.344 (3.95)***	0.193 (10.30)***	0.178 (10.73)***	-0.032 (0.30)	0.286 (1.81)*	0.163 (4.70)***
R^2	0.11	0.06	0.10	0.15	0.14	0.06	0.02	0.01
N	47	37	40	47	47	30	47	47

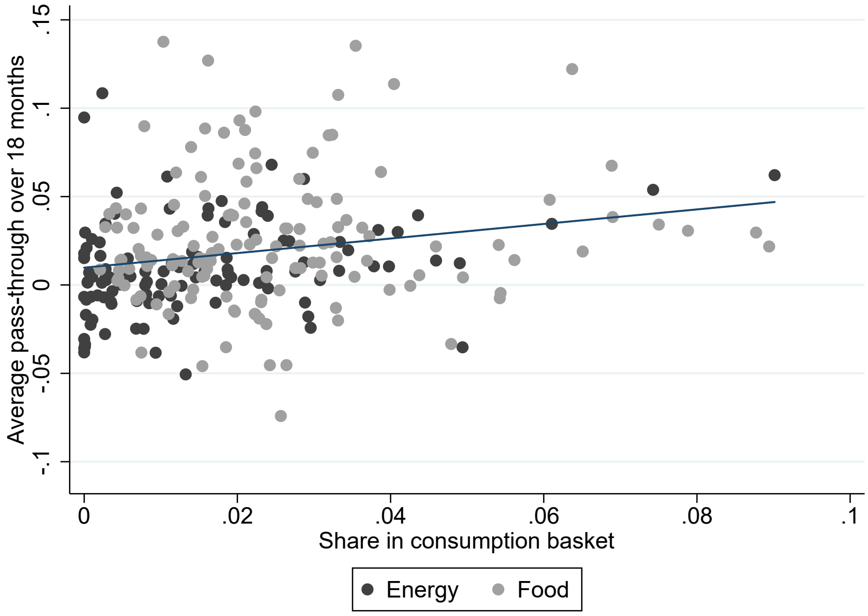
T-Stat in parentheses. Robust standard errors. * Significant at the 10 percent level, ** Significant at the 5 percent level, ** Significant at the 1 percent level.

Table B.5: Regressions of pass-through on type of exchange rate regime and monetary policy

	(1)	(2)	(3)	(4)	(5)
Exchange-rate type (Ref=Floating)					
Non-floating ER	-0.001			-0.086	
	(0.01)			(0.71)	
MP type (Ref=Inflation targeting)					
Other MP		-0.094			-0.069
		(1.03)			(0.42)
Peg		-0.092			-0.100
		(1.16)			(0.91)
CB independence (Ref=Below Median)					
Indep CB > Median			-0.072	-0.202	-0.048
			(1.22)	(1.87)*	(0.30)
Interactions					
Non-floating ER × Indep CB > Median				0.150	
				(1.18)	
Other MP × Indep CB > Median					-0.042
					(0.20)
Peg × Indep CB > Median					-0.000
					(0.00)
Constant	0.192	0.275	0.221	0.294	0.294
	(2.87)***	(3.56)***	(4.38)***	(2.79)***	(2.71)**
R^2	0.00	0.03	0.04	0.06	0.07
N	48	48	39	39	39

T-Stat in parentheses. Robust standard errors. * Significant at the 10 percent level, ** Significant at the 5 percent level, ** Significant at the 1 percent level.

Figure B.5: Correlation between commodity pass-through and share of the commodity in the consumption basket



Note: Scatter plot of the average pass-through over 18 months of selected commodities on the share of associated products in the consumer baskets. Selected commodities include: rice (matched with the share of rice), sugar (matched with the share of sugar), wheat (matched with the share of bread, pasta and pastry), vegetable oils (matched with the share of fats excluding butter), coal (matched with the share of energy excluding fuel and electricity), crude oil (matched with the share of fuels for personal transportation), and natural gas (matched with the share of gas). The dark grey dots represent all items related to energy (crude oil, coal and natural gas), and the light grey points represent all items related to food (cereals, vegetable oils and sugar). The solid line represents the fitted value on the whole sample.

"Sur quoi la fondera-t-il l'économie du monde qu'il veut gouverner? Sera-ce sur le caprice de chaque particulier? Quelle confusion! Sera-ce sur la justice? Il l'ignore."

Pascal

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