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Working Paper Series

#2023-035

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Published 9 October 2023

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UNU-MERIT Working Papers
ISSN 1871-9872

Maastricht Economic and social Research Institute on Innovation and Technology
UNU-MERIT | Maastricht University

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Lost in aggregation? On the importance of local food price data for food poverty estimates

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Abstract

International organizations, governments, and NGOs routinely rely on welfare effect estimates for social programming in crisis situations. Often, these estimation models incorporate national consumer price index data as an integral predictor. This paper contends that utilizing aggregate price data can be misleading due to spatial disparities in price trends. To explore this, we analyze shifts in food poverty estimates by employing local market price data instead of national consumer price index data. Utilizing a dataset from seven West African countries, we highlight significant spatial variation in cereal prices at the local level following the outbreak of COVID-19. Model estimates indicate an increase in food poverty of almost 10% during the pandemic's first wave due to food price increases. Sourcing cereal prices from local markets, instead of national CPI statistics, results in a 5% inclusion and 2% exclusion error, yet similar mean estimates. Our findings underscore the need for systematic collection of local price data for effective policymaking, such as CPI adjustments to social transfers and the allocation of relief funds.

Keywords: Food Prices; CPI; Poverty; Data; West Africa
JEL: D4; E31; Q11;Q18; D4;
Declarations of interest: none

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We utilized ChatGPT for light proofreading assistance during the preparation of this article. Full editorial control and responsibility for the content, analysis, and conclusions presented remain with the authors.

1. Introduction

In recent years, global poverty rates have risen, reversing decades of steady decline (Mahler, Yonzan, and Lakner 2022; Moyer et al. 2022). Current estimates indicate that the pandemic has pushed 90 million people into extreme poverty (Mahler, Yonzan, and Lakner 2022). This situation is further exacerbated by the war in Ukraine, which has added an estimated 71 million to the global poverty count (Ecker, Molina, and Ortiz-Juarez 2022). For monitoring and effective allocation of relief funds to those most in need, international organizations, governments, and NGOs must fully understand the welfare implications of disruptions in international markets. However, this comprehensive understanding is currently lacking. To produce accurate and prompt estimates, many empirical models routinely use national price statistics to gauge household welfare dynamics. This paper argues that relying on national price data might present a skewed picture due to spatial differences in price trends. To underscore this argument, we study the variations in food poverty estimates when using local market instead of national consumer price index (CPI) data.

Changes in food prices significantly affect household welfare on various levels (von Braun 2007; Headey et al. 2012; Rapsomanikis, Hallam, and Conforti 2006). The impact of these price shifts varies based on factors such as geographical location and specific household characteristics. Notably, households that are net food-sellers and those that are net food-buyers often have differing welfare responses to food price increases (Verpoorten et al. 2013; Vu and Glewwe 2011). Additionally, urban and landless rural households are more likely to face notable welfare reductions when food prices rise (Minot and Dewina 2015). Increases in food prices can prompt households to decrease their food consumption or modify their dietary choices, which can have lasting and potentially irreversible nutritional consequences (Anríquez, Daidone, and Mane 2013).

This paper explores the impact of within-country variations in food price dynamics on welfare assessments. Although various methods exist to gauge the effect of food price changes on household welfare, many regional or global studies tend to utilize national-level or global price variations as their input variables (e.g. Headey et al. 2012; Ivanic and Martin 2014; Ivanic, Martin, and Zaman 2012; Wodon et al. 2008; Zezza and Tasciotti 2010). In our analysis, we specifically evaluate how drawing cereal data from markets, as opposed to using national CPI data, alters food poverty estimates, all else being equal. We focus on the cereal price dynamics during the initial wave of the COVID-19 pandemic as our case study and assemble a distinct database that comprises national CPI statistics from seven member states of the West African Economic and Monetary Union (WAEMU), household survey data from the Programme d'Harmonisation et de Modernisation des Enquêtes sur les Conditions de Vie des ménages (PHMECV), and World Food Program market data. Utilizing market-level price data, we determine cereal price trends and identify marked spatial variations in price dynamics across local markets. We then project food expenditures and calorie availabilities using both national and market-level price data. Model estimates indicate an increase in food poverty of almost 10% during the pandemic's first wave due to food price increases. While the overall rate of calorie poverty remains relatively consistent, regardless of the data source, its spatial distribution shows significant differences. Relying on national CPI statistics for cereal prices instead of sourcing from local markets results in a 5% inclusion and 2% exclusion error in calorie poverty estimates. These findings carry notable policy implications, particularly concerning CPI adjustments for social transfers, the distribution of relief funds, and the precision targeting of policy actions during times of crisis.

The use of CPI data to adjust nominal living standard measures has been a topic of debate for years, primarily because CPIs are prone to various sources of measurement bias. Factors such as substitution effects, the introduction of new products, and alterations in product quality can skew living standard estimates (Deaton 1998; Hausman 2003). Moreover, lower-income countries often exhibit low levels of market integration, leading to disparate regional price trends (Dietrich et al. 2022; Mahajan and Tomar 2021). Due to the sampling methodology of price data, CPI weights frequently reflect the consumption patterns of households in the higher income brackets, predominantly in urban areas. Over time, changes in the cost of living in these areas may diverge from rural trends, influencing estimated poverty trajectories. For a comprehensive discussion on biases introduced by CPI in poverty estimates, refer to Dabalen, Gaddis, and Nguyen (2020) and Gaddis (2016). Diverging from past studies, we utilize market-level price data to emphasize the consequences of using local over national price data. This distinction is crucial as prices for food staples can differ significantly even within proximate areas. Such disparities can arise from poor infrastructure and elevated transportation costs (Brenton, Portugal-Perez, and Régolo 2014; Salazar, Ayalew, and Fisker 2019; Shively and Thapa 2017), inadequate storage capabilities (Andersson, Bezabih, and Mannberg 2017; Huss et al. 2021), or uncertainties surrounding prices and trade-related risks (Chavas and Nauges 2020), escalating trade barriers between market regions. However, even when arbitrage operations are viable, comprehensive knowledge of regional price differentials often remains elusive (Aker 2010). Numerous studies pinpoint asymmetric price fluctuations post the pandemic's onset, contingent on factors such as market integration levels (Dietrich et al. 2022), proximity to production sites (Mahajan and Tomar 2021), or specific commodity types (Bairagi, Mishra, and Mottaleb 2022). In this paper, we delve into the welfare repercussions of these non-uniform price trends by employing WFP cereal market price data, juxtaposing our findings against a benchmark approach reliant on national CPI statistics. Our analysis reveals that national CPI data obscure local variations; while this doesn't alter aggregate poverty figures, it does significantly influence the distribution of impact estimates.

Furthermore, our study advances the extensive literature that examines the impact of global price shocks on consumer welfare (Cudjoe, Breisinger, and Diao 2010; Dillon and Barrett 2016; Minot 2014). Existing evidence suggests that the surge in commodity prices on international markets beginning in 2008 heavily influenced consumer prices in lower-income countries (Abbott and Borot de Battisti 2011). The global shock most profoundly affected the poorest households (D'Souza and Jolliffe 2014; Kumar and Quisumbing 2013; Wodon et al. 2008) and also induced secondary effects, such as social unrest (Bellemare 2015). These developments prompted heightened efforts by governments and international bodies to stabilize prices. Yet, a decade later, international prices are surging once more, exerting even greater pressure on consumer prices (Narayanan and Saha 2021), exacerbating poverty (Arndt et al. 2023), and intensifying food insecurity (Vos, McDermott, and Swinnen 2022). The unparalleled disruptions instigated by the pandemic compelled policymakers worldwide to balance the risks associated with virus transmission against the economic consequences of mobility limitations. High-quality data is instrumental in guiding such policy decisions, but timely information is often lacking, particularly in lower-income nations. In this paper, we posit that systematic price monitoring at the local level is an invaluable tool, crucial for enhancing our comprehension and tracking of the intricate welfare dynamics that global shocks can precipitate.

Lastly, this paper adds to the literature on welfare mapping, which capitalizes on the rapidly growing availability of new data sources and techniques. Such methods can help direct public resources, especially in many lower-income countries where timely and accurate survey data is often lacking. For instance, the merging of various satellite imagery sources has been employed to predict welfare indicators with increasing success and granularity (Jean et al. 2016; Smythe and Blumenstock 2022). Moreover, emerging data sources like phone metadata (Aiken et al. 2022) and social media content (Ledesma et al. 2020) have been harnessed for wealth mapping tasks. However, these data sources are less appropriate for scenarios requiring household-level welfare estimates or for modeling short-term wealth dynamics, such as those triggered by the pandemic. In such instances, food prices offer a potent signal that encapsulates vital information for understanding welfare trajectories, as demonstrated in food security forecasts that, among other factors, utilize food price data (Martini et al. 2022). In this paper, we delve into how varying price input data can skew food poverty estimates. Our findings emphasize the importance of systematically collecting local price data, a crucial element for welfare monitoring. Similarly, Villacis et al. (2023) explored how variations in recall periods in food security measures influence predictions. Unlike their study, our focus is on an input variable, and price aggregation processes. This is significant as national CPI data typically serve as the foundation for adjusting transfer values and more broadly guiding policy interventions.

The rest of the paper is structured as follows: Section 2 outlines the data compilation process. Section 3 presents the observed price dynamics during the study period, along with a comparison of welfare estimation discrepancies arising from different cereal price data sources. The final section delves into the implications of our results.

2. Data

Our main analysis centers on cereal price trends. Using multiple data sources, we constructed a distinct database comprising comprehensive food price data and household survey data from the PHMECV program. This allows us to scrutinize the impact of price data aggregation on welfare estimates. The dataset encompasses Benin, Burkina Faso, Côte d'Ivoire, Mali, Niger, Senegal, and Togo.[1] Below, we offer a more in-depth description of the data sources and Figure 1 provides a visual overview of the data sources and data compilation steps.

Market-Level WFP and country-Level CPI Price Data

In the analysis, we contrast the official national CPI statistics with the more granular market-level cereal price data from WFP. In countries where WFP operates, the organization compiles sub-nationally disaggregated data on food commodity prices. This data is a combination of primary and secondary data collection efforts. Moreover, WFP collaborates with national statistical offices for digitalizing market price data through capacity-building activities, making the information publicly available on the corporate DataViz portal.[2] The commodities frequently surveyed include wheat, maize, rice, oil, and beans. The list of surveyed commodities has seen expansion, notably in 2019, in response to the Scale-Up Nutrition

[1] The selection of these countries was driven by the accessibility and compatibility of data sources. Guinea Bissau was excluded from the database due to the limited number of market data points in the WFP database.
[2] World Food Programme Global Market Price database, Dataset downloaded from https://dataviz.vam.wfp.org on 11/06/2022. For sampling guidelines refer to https://www.wfp.org/publications/collecting-prices-food-security-programming-how-why-price-data-collection-wfp-march-2017.

movement and the wider adoption of a multi-sectoral framework by many UN organizations and governments.[3]

For the seven countries covered in our study, retail prices of cereal items are available from 259 markets in the research region. While the database also contains information on other commodities, our main analysis focuses on cereals as they have by far the best coverage. Data availability varied markedly among countries; from 4 commodities and 6 markets in Togo to 48 commodities and 81 markets in Mali. While some of the price information dates back to 1990, we use price developments from January 2019 onwards, when a substantial number of new commodities was added for most countries under review. While the coverage of commodities varies by markets, cereals are the main staple food and its prices collected in all markets. Therefore, we focus the main analysis on cereal prices and only as additional robustness check consider market prices of other food groups.

We supplement our database with country-level CPI price data. These data come from the economic area's harmonized consumption price index system, provided to us by the WAEMU secretariat. They represent monthly price levels relative to 2014 levels across 35 food categories. These data are nationally aggregated and cover the period from early 2018 to the end of 2020. The underlying data are collected monthly for a total of 652 food items.

Household food consumption data and Stone price indices

To assess dietary preferences in each enumeration area, we utilize household survey data from the PHMECV program, a collaboration between the World Bank and the WAEMU

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[3] World Food Programme interpreted this framework, and the relevant collection of commodity price data through the essential needs guidelines https://www.wfp.org/publications/essential-needs-guidelines-july-2018

Commission. These surveys were carried out across all WAEMU nations in two phases: the initial phase spanned from October to December 2018, and the subsequent phase ran from April to July 2019. The rationale for the two-phase approach was to capture seasonal consumption variations. These surveys offer detailed, nationally representative data on 53,967 households, and they are accessible via the World Bank's Microdata library. Given the uniform survey tools utilized across the countries, results offer a consistent level of comparability. Further details on the data collection timeline, sample size, and basic statistics by country can be found in Appendix Table A1.

We utilize the food consumption module from the surveys, which documents details on quantity, value, and origin of consumption for 19 cereals, alongside 119 additional food items, all recalled over a period of seven days. From this data, we deduce the price per kilogram a household expended on cereals (as well as other food items). We tag consumption data as outliers if the price per kilogram of a food item deviates by more than two standard deviations from the median value for that country. In such instances, the consumption per adult equivalent and the price per kilogram are adjusted to align with the national medians.

In line with the FAO-WFP guidelines, we group food items into cereals and nine other categories based on their nutritional properties (Hatløy et al. 2000; Hoddinott and Yohannes 2002). These categories are: "Cereals", "Tubers and Roots", "Pulses", "Fish and Meats", "Vegetables", "Fruits", "Fats (including edible oils)", "Dairy", "Sugar and condiments (including salt and other sugary products)", and "Beverages and other food items". The distribution of food category budget shares by country is detailed in the Appendix Table A2.

In our study, we utilize the prices and consumption weights from the PHMECV dataset to infer local dietary preferences, which in turn aids us in determining trends for food category prices.

A principal price metric in our analysis is the kg-weighted Stone prices.[4] These are defined as weighted prices per kilogram for each food category within a particular enumeration area. To derive these Stone prices, we use weighted averages of the kg-prices associated with the individual items in a food group. The weight for each item is based on its proportional representation in the total physical consumption for that enumeration area. For determining a food item's kg-price within an enumeration area, we resort to its median price if there are at least three observations in that area. If fewer than three households report consumption of that item in the area, we then look to the departmental median price, provided there are at least three observations at that departmental level. If this criterion isn't met, we default to using the median price across the entire survey.

Using the household survey dataset, we're able to gauge consumption patterns for cereals along with other food products, and this further enables us to compute Stone prices at a specific time snapshot. To monitor the evolution of these Stone prices across a timeline, we draw upon both country-specific and market-specific price data. This data is then paired with details regarding consumption preferences.

Price developments

A food group's price development is the weighted mean price development of corresponding items in the price databases. The food items in the WFP and WAEMU data are weighted according to consumption preferences in the PHMECV data, both on the national and enumeration area levels. Commodities not covered in the other data sources are matched

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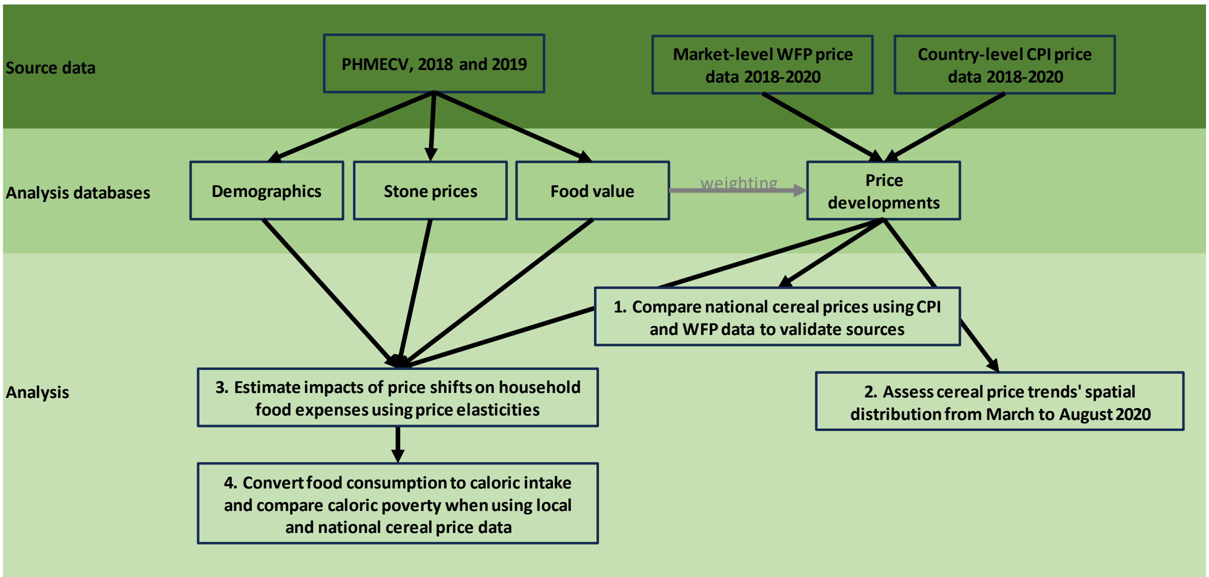
[4] For household food consumption where we lack specifics on the individual food items or groups consumed, we exclude this from the Stone prices computation. However, when estimating the kcal availability for households, this consumption is taken into account. We make the assumption that its distribution across food groups mirrors the patterns of in-house food consumption.

with the average price development of the food group's commodities in the price data. In other words, we weigh items by consumption preferences at the respective level of analysis to ensure that more important commodities receive a larger weight in determining price developments. The tables used for matching PHMECV and other commodities are provided in Appendix Table A2. As mentioned, we focus the main analysis on cereal price developments due to market data coverage limitations but extend the analysis to all available market-level price data as a robustness check.

Figure 1 Overview of data compilation and analysis steps



3. Results

The analysis is presented in four main steps, as highlighted in Figure 1. First, we compare cereal Stone price trends using the WAEMU and WFP datasets, noting that both sources yield similar national price trends. Following that, we look into the spatial variations in cereal prices within the WFP market data during the pandemic's first wave. In our third step, we evaluate the impact of this price change on real food expenditures and analyze how estimates shift when we use market-level cereal prices in place of national data, keeping all other factors constant. Finally, we transform these food consumption figures into caloric intake to demonstrate the effect on food poverty estimates when opting for market-based cereal data over national statistics. The specifics of our methods are detailed in the subsequent sub-sections.

(I) Cereal Stone Price Trends

For the comparison of cereal Stone price trends, WFP Stone prices are aggregated to the national level, giving each market in a country equal weight.[5] We analyze the resulting time series and the CPI-based one from January 2019 to the end of 2020. This offers comprehensive market coverage and encompasses a period of significant price volatility during the Covid-19 pandemic. Time series are normalized to 1 in January 2019 – the year preceding the onset of the Covid-19 pandemic.

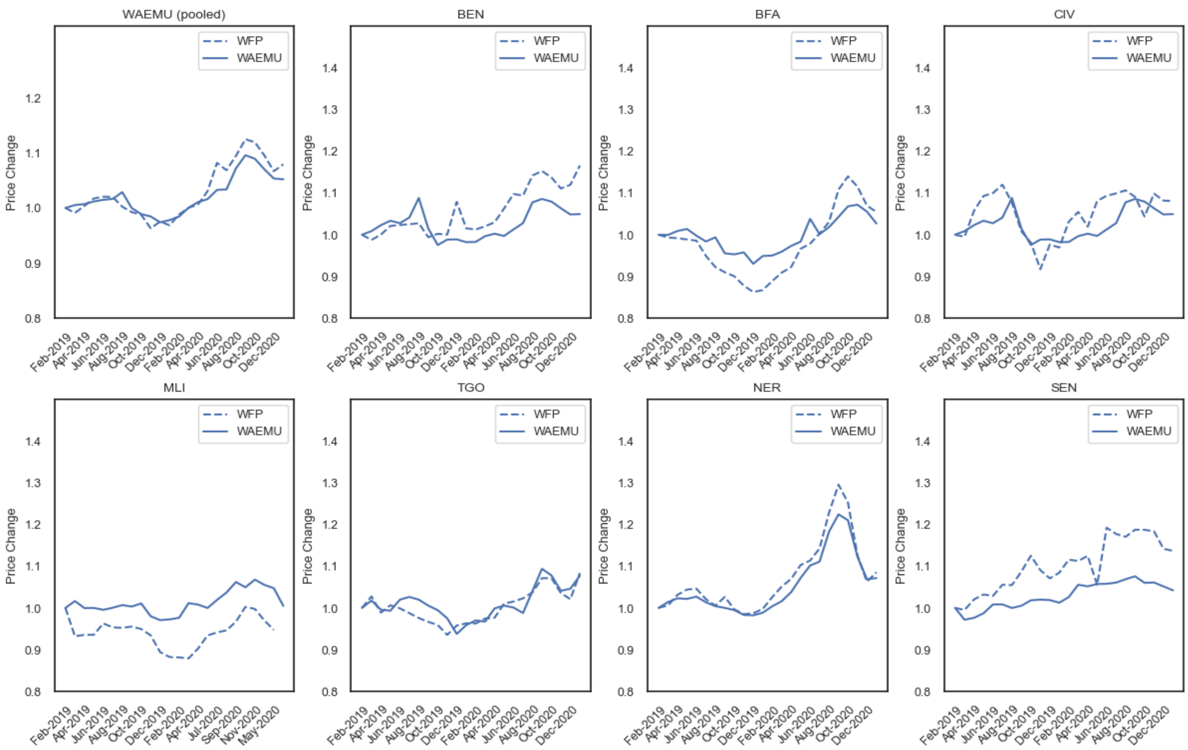
Figure 2 presents both time series by country. The graph reveals steep surges in national cereal prices following the emergence of the pandemic in 2020, with varying intensities across countries. Most strikingly, in Niger, cereal prices soared by over 20 percentage points (pp) from March 2020 to July 2020. In Mali, Togo, Benin, Cote d'Ivoire, and Burkina Faso, price hikes hover around 10pp during this timeframe, while Senegal experienced a relatively subdued increase. When considering the aggregated data from all seven countries, there's a rise just above 10pp towards the end of the pandemic's first wave, which begins to recede post-August.

[5] We refrain from weighting markets for example by population densities because we would need to assume that all markets have equally sized market catchment areas or we would need to estimate market catchment areas separately for each market which is not trivial.

The graph further indicates that trends derived from the aggregated WFP market data closely align with the official national CPI statistics. In countries with a vast number of sampled markets, such as Mali and Burkina Faso, the price trends are almost identical. The most pronounced discrepancies between the two time series are evident in Senegal, with variations reaching up to 10pp. Nonetheless, the dynamics of the time series remain strikingly parallel. For instance, the price escalation between April and August 2020 is consistent in both the national CPI statistics and the WFP market data.

The results suggest that aggregating the market-level cereal price data yields comparable dynamics to the official national CPI data for the region. While these trends specifically focus on cereal prices, which are well-represented at the market level, similar results were obtained for other food groups. This suggests that the patterns observed aren't uniquely influenced by the specific traits of cereal prices.

Figure 2 Cereal price developments in national and market data



Source: own calculations based on WAEMU CPI and WFP market data. **Notes**: Price change calculated in relation to benchmark price on January 2019.

(II) Spatial Distribution of Prices

In Figure 3, we visually detail the shifts in cereal Stone prices across each WFP market from April 2020, marking the onset of the pandemic, to the close of its initial wave in August. The figure incorporates 259 colored markers, each pinpointing a distinct WFP market, with grey markers representing the PHMECV enumeration areas. The size of each colored marker corresponds to the change in the cereal Stone price within that period. Larger markers indicate markets experiencing pronounced price augmentations. Red markers denote markets where prices rose, while yellow markers represent those where prices dipped.

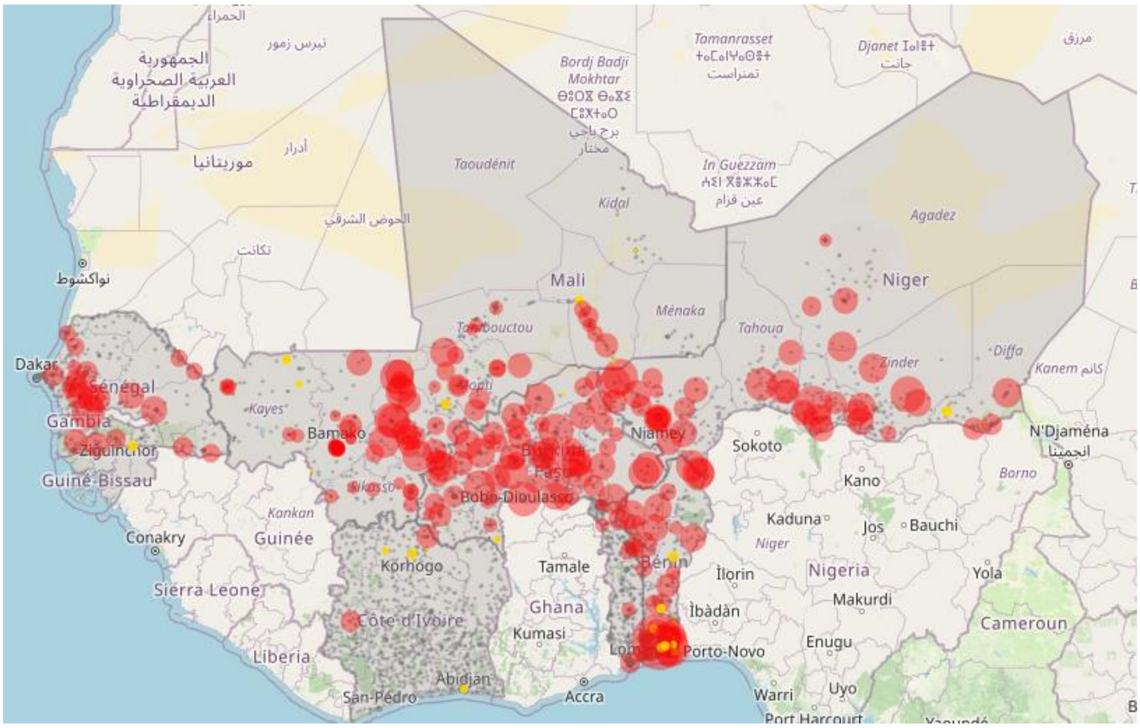
On a countrywide average, Niger experienced the most pronounced escalation in cereal Stone prices, at 17pp. Burkina Faso follows closely with an upturn of 15pp. In contrast, Cote d'Ivoire saw a minimal rise of only 2pp. Despite these averages, there's a substantial intra-country variation in price shifts. As an illustration, Burkina Faso's market price shifts spanned from a decrease of 10pp to an increase of 35pp.

When observing the standard deviation of these price alterations, Burkina Faso, Benin, Mali, and Cote d'Ivoire all recorded around 10pp. Togo stood out with the most constrained deviation, at 4pp. This limited variation in Togo might be due to the dataset encompassing merely six markets, potentially not providing a comprehensive view of the country's price dynamics.

To statistically test the difference between market and national prices, we rely on Wilcoxon signed-rank tests. For every month from April to August 2020 and for every market, we compute the difference between the market and the aggregated national price change and test whether the distribution of the differences is symmetric about zero. The test statistic leads us to reject the null hypothesis that the effects are not different at the 0.1% significance level in the region. If we break it down by country, the test statistics remain significant for all countries except for Cote d'Ivoire where only a few market data points are available. This underscores the visual evidence suggesting statistically significant spatial differences in cereal Stone price trends.

As expected, markets that are closer to each other tend to have more similar trends in the observed period. However, this spatial correlation is weak. To better understand the spatial relationship in price trends, we fitted a variogram that uses the pairwise distances between all markets and models the similarity in price trends as a function of market distances (Bohling 2005). Therefore, we first computed the distances between all market pairs in a country and calculated the similarity in price trends between each pair. The scatter plot of price dissimilarity and the distance of pairs shows no clear spatial correlation patterns (see Figure A3). In several instances markets that are close to each other even experienced very different trends (see for example, Benin). This is not too surprising given that strict lockdown measures and mobility constraints during the first pandemic disrupted trade activities immensely, rendering distances between markets less important. National CPI data mask these local differences, which can affect policy decisions and result in avoidable welfare losses further downstream. To better understand the differential welfare impacts, we next turn our attention to household responses to changing prices.

Figure 1 Cereal Stone Price Change August – April 2020 by market



	MLI	NER	BFA	CIV	SEN	TGO	BEN
Mean	0.07	0.17	0.15	0.02	0.12	0.06	0.09
StD	0.10	0.07	0.10	0.10	0.06	0.04	0.11
Min	-0.22	-0.00	-0.10	-0.11	-0.00	0.02	-0.06
Max	0.30	0.35	0.36	0.15	0.27	0.12	0.5
# markets	81	40	59	6	22	6	45
Rank test p-val.	0.00	0.00	0.00	0.11	0.00	0.03	0.00

Source: own calculations based on WAEMU CPI and WFP market data. **Notes**: Markers represent markets sampled by WFP (red=price increase; yellow=price decline). The larger the radius the larger the Stone price increase between April and August 2020 in that market. Grey points show PHMECV enumeration areas. The signed rank test tests the null hypothesis that differences in market prices compared with the national mean are zero against the alternative hypothesis that they are different from zero pooling the months April to August.

(III) Welfare Impacts of Price Changes

To shed light on the welfare impacts of these price changes, we model how household food expenditures react to increasing prices. Thereafter, we feed national CPI data into the model to estimate how food expenditures are impacted by changes in Stone prices during the first wave of the pandemic—our benchmark model estimates. Lastly, we replace national cereal CPI data with market-level cereal prices to illustrate how disaggregated cereal price data impacts the estimates. By comparing the differences in the resulting estimates, we aim to show the extent to which national-level data conceal regional differences in welfare estimates.

Household Responses to changing Food Prices

For the modeling, we rely on pre-pandemic 2018-2019 PHMECV survey data to estimate households' responses to changing prices. The model's design follows practices commonly used by academic papers to model welfare impacts of price shocks (Attanasio et al. 2013; Dietrich and Schmerzeck 2022; Ecker and Qaim 2011; Tiberti and Tiberti 2018).[6]

We model the demand for food with a two-stage budgeting procedure. In the first stage, we assume that households allocate resources between food and non-food goods. In the second stage, food expenditures are allocated across the ten food categories. We use a standard demand system to model how households allocate resources to each of the ten food categories as a function of the household's food expenditure budget, food prices, and household characteristics (Deaton and Muellbauer 1980). We parameterize the demand system with a Quadratic Almost Ideal Demand System (QUAIDS), as suggested by Banks, Blundell, and Lewbel (1997). In essence, the budget shares ww for each of the ten food categories ii are modeled as a function of the log Stone prices *p*, household food budget *m*, and demographic household characteristics:

[6] To test the quality of our food expenditure predictions and to compare different specifications, we use a k-fold validation approach with 8 folds. We compute the R^2 comparing actual and predicted expenditure as prediction performance metric. The average R^2 over all countries, wealth groups and folds indicate that our model explains 97.6% of the variation in food expenditures. While not specific to the dynamics during the pandemic, it suggests that the model is able to capture responses to past price changes well.

$$w_i = \alpha_i + \sum_{j=1}^{k} \gamma_{ij} \ln p_j + \beta_i \ln\left\{\frac{m}{a(p)}\right\} + \frac{\lambda_i}{b(p)}\left[\ln\left\{\frac{m}{a(p)}\right\}\right]^2 \qquad (1)$$

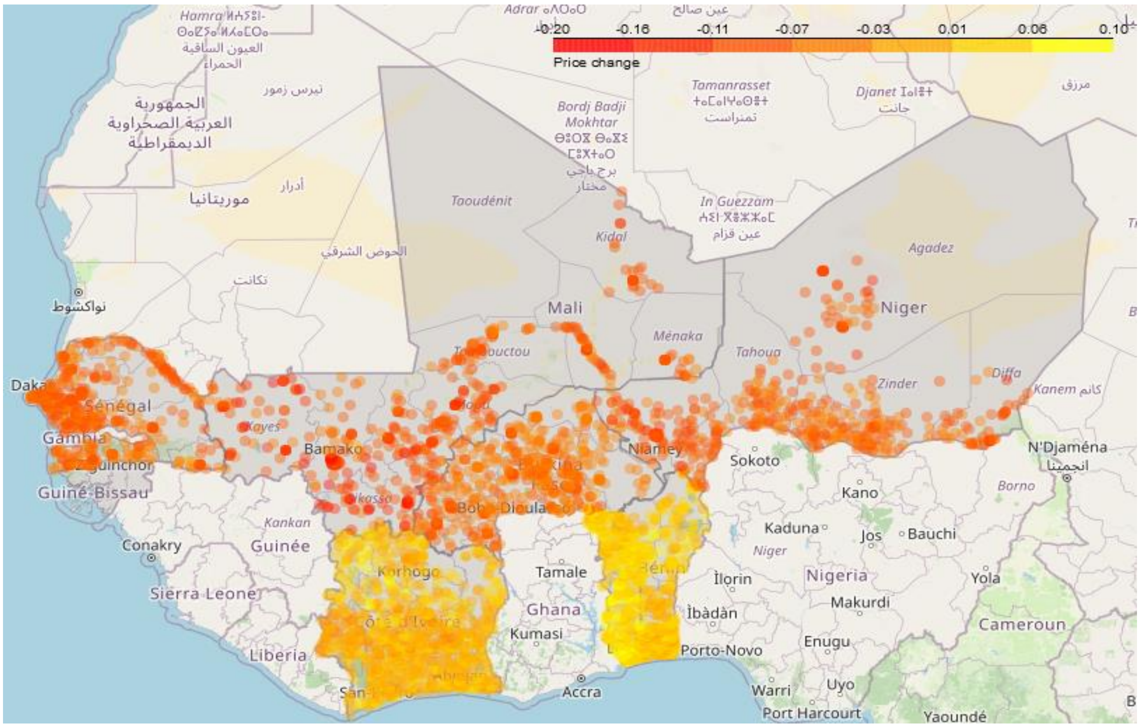
where *ln a(p)* and *b(p)* are price aggregators conditional on which budget shares are linear in *ln p* and *ln m*. The behavioral assumption restrictions in the model ensure that budget shares sum up to one through the adding-up condition of constants to one and homogeneity reflected in log price parameters summing up to zero as well as symmetry in price responses. To account for differences in price responses between countries, we estimate separate models by country.

Food Expenditure Impact Estimates (CPI data only)

With the model, we estimate how the real value of food expenditures changed between April and August 2020 in each PHMECV enumeration area. Figure 4 maps the relative changes using national CPI data – the benchmark model. The color of the markers is relative to the predicted change in real food expenditure changes, where the shade of red refers to welfare reductions and yellow to increases.

The map indicates pronounced differences between countries. On the one hand, the real value of food expenditures declined notably, by slightly less than 10pp, in Senegal, Mali, Niger, and Burkina Faso on average. On the other hand, in Côte d'Ivoire, Benin, and Togo, the estimates suggest even slight increases of up to 4pp. These two distinct impact clusters are related to differences in price increases in the 10 food categories and also to differences in responses of households in various regions. Price changes of all 10 food groups and the estimated demand elasticities to increasing food prices are provided in Appendix Table A4. While there are pronounced differences between the two clusters, there is little variation within countries, and the standard deviation of cluster-level changes in real food expenditure only ranges from 2pp to 3pp. In other words, the model estimates suggest that the impacts of price changes on real food expenditures were rather evenly distributed within countries. To explore if this is related to the price input data, we repeat the prediction exercise but replace the national cereal CPI data with local cereal prices for the predictions, keeping all else the same.

Figure 2 Change in real food expenditure between April and August 2020 (only national prices)



	MLI	NER	BFA	CIV	SEN	TGO	BEN
Mean	-0.10	-0.09	-0.06	0.01	-0.07	0.04	0.02
StD	0.03	0.02	0.02	0.02	0.01	0.02	0.02
Min	-0.22	-0.15	-0.1	-0.05	-0.09	-0.00	-0.02
Max	-0.03	0.02	-0.01	0.09	-0.02	0.1	0.1

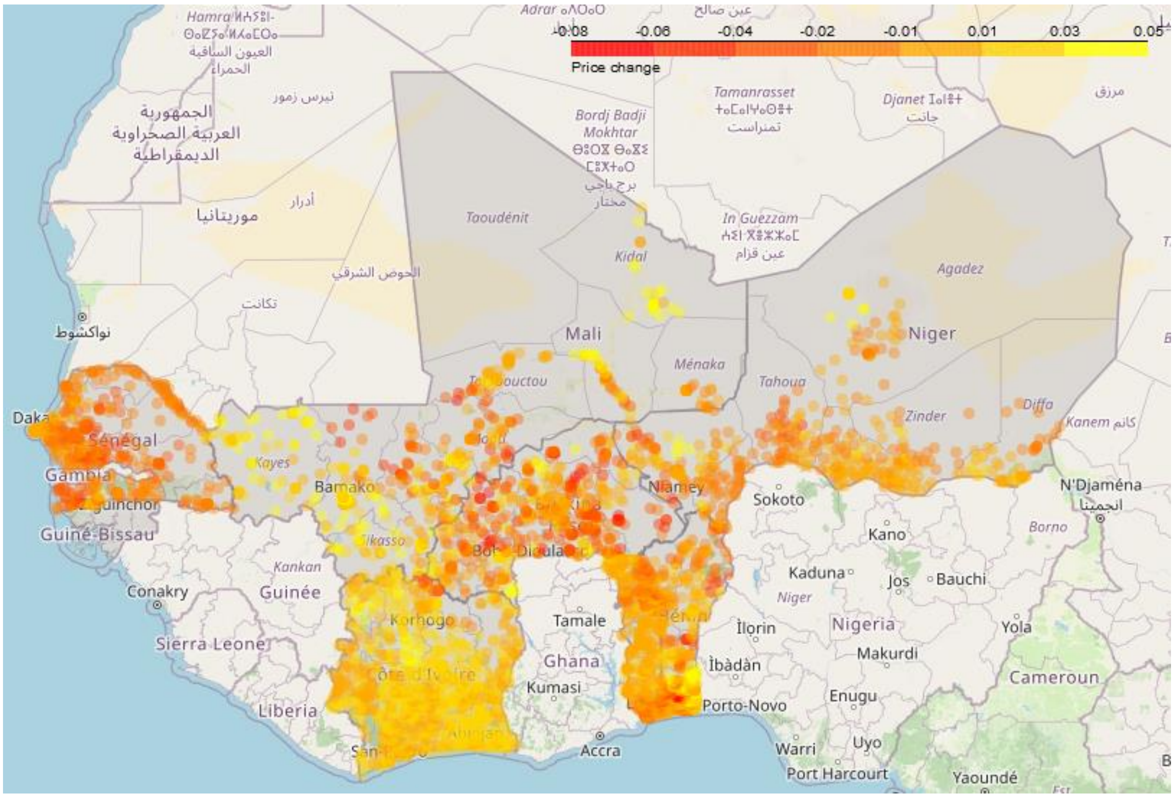
Source: own calculations based on WAEMU CPI and WFP market data. **Notes**: own calculations based on PHMECV data, CPI and WFO price data. Points show means auf prediction difference in 53132 PHMECV enumeration areas if cereals are sourced from closest WFP markets divided by prediction with CPI data only.

Food Expenditure Impact Estimates (Cereal prices sourced locally)

Figure 3 maps the change in predictions after replacing national CPI cereal price data with the closest WFP market cereal price data. On average, there is little difference in aggregated predictions between the models with WFP cereal market data and the benchmark model that only uses national CPI data. An exception is Mali, where the market-level data lead to a 6pp larger impact estimates compared with the benchmark model, which seems to be driven by a few enumeration areas with large differences. However, it is important to keep in mind that we only change the measurement source of cereals and keep the other nine food categories the same.

Despite the similarity in mean estimates, there is remarkable variation in predictions within countries. For example, in Mali, the differences in predictions between the market-level and benchmark model range from -13pp to 39pp, with a standard deviation between enumeration areas of 6pp. This result is quite considerable given that we only changed the price information of one commodity group. In Niger, Burkina Faso, Benin, and Senegal, the standard deviation ranges between 2pp and 3pp; but, even in this case, it is possible to observe significant differences in predictions between the market-level and benchmark model range (see Figure 3). As expected, in Cote d'Ivoire and Togo, where only cereal price information from 6 markets is available, the difference to the CPI predictions is lowest. However, signed rank tests suggest that the difference in consumption predictions between both models is statistically significant in the pooled data but also in each country when tested separately.

Figure 3 Difference in predicted food expenditure change with national cereal CPI and with local cereal price data



	MLI	NER	BFA	CIV	SEN	TGO	BEN
Mean	0.06	0.01	-0.00	0.02	-0.01	0.00	-0.01
StD	0.06	0.03	0.02	0.01	0.02	0.01	0.02
Min	-0.13	-0.12	-0.10	-0.07	-0.07	-0.03	-0.11
Max	0.39	0.21	0.16	0.11	0.06	0.03	0.11
Number of markets	81	40	59	6	22	6	45

Source: own calculations based on WAEMU CPI and WFP market data. **Notes:** own calculations based on PHMECV data, CPI and WFO price data. Points show means auf prediction difference in 53132 PHMECV enumeration areas if cereals are sourced from closest WFP markets divided by prediction with CPI data only.

(IV) Food Poverty Rates

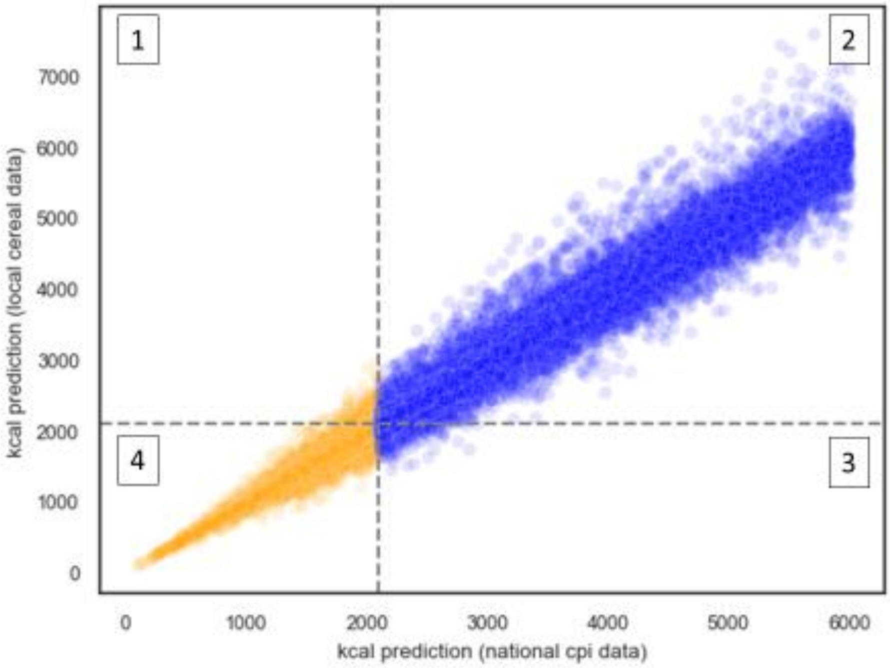
In the final step of our analysis, we proceed to estimate food poverty rates using both models. To accomplish this, we calculate adult equivalent calorie availability based on the physical weight of a household's consumption and food groups' average energy density. A food group's energy density, that is, the kcal available per kilogram, is calculated from the PHMECV calorie conversion table, with individual food items weighted by national consumption preferences. To obtain the kilogram weight of a household's consumption of a certain food group, different strategies are applied for different food sources. For self-produced goods, the weight is assumed to remain equal to that in the PHMECV survey. For gifted and bartered goods, as well as for out-of-household food consumption, the nominal value is assumed to remain equal to the PHMECV one, and the weight is obtained by dividing the nominal value by current Stone prices. As there is no food group information for out-of-household consumption available, it is assumed to be divided among food groups according to the household average. Purchased household consumption is treated similarly to gifts and barter, except that the nominal value is simulated using our models. Finally, household calorie availability is normalized using FAO adult equivalents. Based on these estimates, households falling below the 2100 kcal per adult equivalent threshold are classified as food poor. Using this approach, we estimate food poverty both for the benchmark model that exclusively relies on national CPI data, and the model that incorporates cereal Stone price data sourced from the nearest market.

As expected, food poverty estimates see an increase in from April to August in the region by about 2.5pp or 10% to a food poverty rate of 26% in the research region. As suggested by the previous results, the rise is most pronounced in Niger (7pp) and lowest in Senegal and Togo (1pp) using the benchmark model with national CPI data. These estimates gibe an idea how the soaring prices during the first wave of the pandemic stressed regional food security.

In Figure 4, we present a scatter plot showing the poverty estimates for August 2020, comparing these benchmark estimates with the model sourcing cereal prices from markets. The orange points on the plot represent individuals classified as food poor according to the benchmark model, while the blue points represent non-poor individuals. Deviations from the diagonal line in the plot indicate differences between the estimates produced by both models. As discussed, 26% of individuals are classified as food poor in August 2020 according to both models. Notably, Burkina Faso, Cote d'Ivoire, and Togo exhibit the highest food poverty estimates, with around 30% of the population falling under the food poverty threshold. Conversely, Senegal, Mali, and Benin exhibit the lowest food poverty estimates, with 18% and 19% of the population classified as food poor. Across all countries, the mean of food poverty estimates generated by both models are similar, differing by no more than 2 pp.

Despite the overall similarity in aggregated food poverty rates between the two models, there are notable discrepancies in the distributions. Specifically, 5% of individuals classified as food poor according to the benchmark model are not identified as such in the alternative model. This inclusion error rate corresponds to the number of observations in quadrant 1 divided by the sum of observations in quadrants 1 plus 4 in Figure 4. Additionally, 2% of individuals classified as non-poor according to the benchmark model are classified as food poor if local cereal price data is used. This exclusion error rate corresponds to the number of observations in quadrant 3 divided by the sum of observations in quadrants 2 plus 3.

Figure 4 Predicted calorie intake in August 2020 with CPI versus market cereal prices



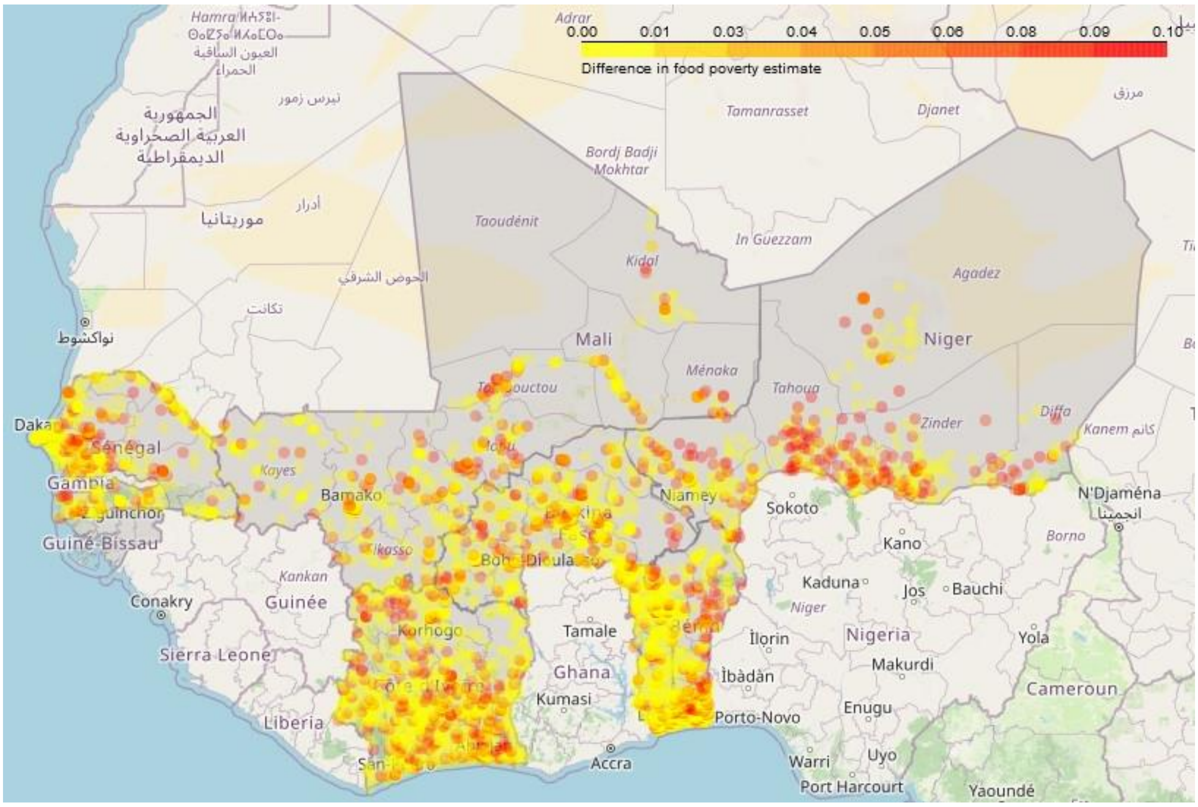
	MLI	NER	BFA	CIV	SEN	TGO	BEN
Food Poverty (national CPI only)	0.18	0.24	0.32	0.33	0.18	0.35	0.19
Food Poverty (cereal market data)	0.17	0.26	0.32	0.31	0.20	0.35	0.20
Inclusion Error	0.09	0.04	0.04	0.07	0.01	0.01	0.05
Exclusion Error	0.01	0.05	0.02	0.00	0.03	0.01	0.02
N	159448	144576	168240	311808	171744	148104	192288

Source: own calculations based on WAEMU CPI and WFP market data. **Notes:** Results based on predicted calorie consumption and a food poverty threshold of 2100 kcal. For better visibility, kcal values above 6000 are not shown in the scatter plot. Inclusion and exclusion errors refer to number of individuals predicted non-poor and poor respectively with benchmark model but poor and non-poor respectively with model that used market level cereal prices. Inclusion Error = #1/(#1+#4); Exclusion Error=#3/(#3+#2).

These error rates vary across countries, with Mali demonstrating the most extreme case. In Mali, 9% of individuals classified as food poor according to the benchmark model are not classified as poor in the model incorporating market cereal price data. This suggests that when accounting for local price trends, the distribution of food poverty undergoes substantial changes, despite maintaining a similar overall poverty count. In Niger, the highest level of inclusion error is observed. Out of the 79% of individuals classified as non-poor according to the benchmark model, approximately 4% would be classified as poor when market cereal price data are utilized. Conversely, Togo exhibits the highest level of overlap in poverty classifications between the two models, with only a small percentage of classifications differing as it has the least dense network of market data available.

A visual inspection of the spatial distribution of estimation discrepancies between both models does not reveal any clear pattern that would suggest that certain regions or zones are more prone to misclassification (see Figure 5). Instead, it is the combination of market-level data availability and diverging price trends that describe discrepancies, which are not equally distributed across enumeration areas.

Figure 5. Food poverty discrepancy in estimates using market versus national cereal price data



Source: own calculations based on WAEMU CPI and WFP market data. **Notes:** Results based on predicted calorie consumption and a food poverty threshold of 2100 kcal. The darker the shade of red, the higher the discrepancy between estimates per show PHMECV enumeration areas.

4. Conclusion

Food prices embody important local information in market economies, serving as a powerful indicator of welfare dynamics. Leveraging local price data allows for estimates to more accurately capture the spatial variations in welfare dynamics, thereby guiding policymakers and enhancing the effectiveness of policies aimed at improving food security. Thus, our results advocate for the systematic collection of local food price data, which should ideally encompass a dense network of markets and cover a broad array of commodities.

Although our results emphasize the significance of market price data, several limitations must be recognized: our analysis is focused on certain facets of household welfare and does not seek to provide a comprehensive assessment of all welfare impacts. Firstly, the models only alter cereal prices, leaving all other prices at national averages. However, when the analysis is expanded to include market data for all food categories available in the nearest market, not just cereals, our estimates do not change significantly. Secondly, the analysis concentrates on short-term impacts and does not consider long-term adaptations to changing prices, for instance, in forms like changes in livelihoods or agricultural production. Thirdly, our analysis hones in on purchased household food consumption, which accounts for an average of 53% of total household expenditures in the 7 countries in our sample, and assumes short-term constancy in food availability from other sources. In essence, we view price changes as an exogenous supply shock and maintain all else (including household incomes) constant in the short-term. Fourthly, we examine the consumer impacts of price changes without modeling the positive effects of rising prices for food commodity sellers. Despite these limitations, our study highlights the intrinsic issues with data aggregation. Welfare estimates that depend on country-level price aggregates may underestimate the spatial variance of welfare losses and potentially lead to suboptimal allocation of relief efforts. However, national poverty rate estimates do not shift significantly, whether cereal data are sourced locally or nationally. Therefore, the choice of data source has vital implications for the distribution of poverty estimates but, in our case, does not notably impact poverty rate estimates.

This study demonstrates that West African price dynamics during the pandemic have not been uniform, which distorts poverty estimates reliant on national CPI data. This is crucial because, in crisis situations, face-to-face welfare data collection is often unfeasible, and policymakers must depend on estimates for timely decision-making, such as determining where and how to allocate relief resources.

While the pandemic has been surpassed, new shocks are impacting West Africa with severe welfare implications for food security. Poor rains in the last two years have led to significant cereal production deficits, further complicated by disruptions on international commodity markets due to the war in Ukraine. Current estimates of the share of food insecurity range between 11% and 15%, with the deteriorating security situation and political tensions posing serious threats to regional welfare.

To adjust existing policies, such as cash transfers, to a context of rising prices, or to design new policies aimed at targeting communities most severely hit by shocks, knowledge of the dynamics of the cost of living is required. Using national CPI data to approximate trends works on average but fails to identify sometimes strong spatial variations in local trends. The findings of this research underscore the need for continuous and detailed collection of local price data as a relatively cost-efficient tool of welfare monitoring activities. In times of multiple crises, the availability of real-time data is crucial for welfare monitoring and defining policies.

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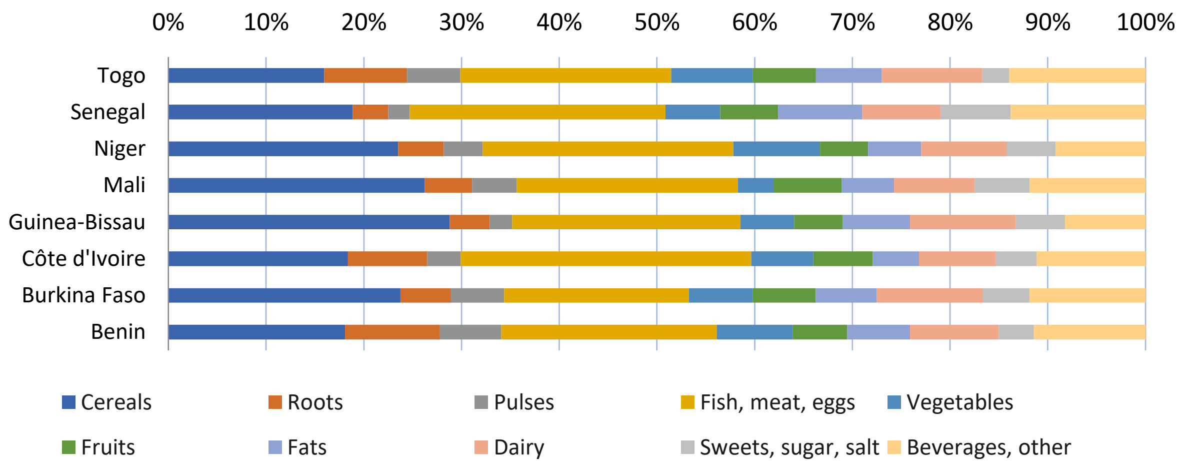
Annex

Table A1 Overview of PHMECV data

	collection period	sample size	% kg-price outliers	% poor	% rural
Benin	Oct 2018 – Jul 2019	8012	4.7	30.6	53.4
Burkina Faso	Aug 2018 – Jul 2019	7010	4.1	31.5	68.7
Côte d'Ivoire	Sep 2018 – Jul 2019	12992	4.6	28.0	47.5
Mali	Oct 2018 – Jul 2019	6602	5.4	34.8	71.7
Niger	Oct 2018 – Jul 2019	6024	5.0	32.5	82.9
Senegal	Sep 2018 – Jul 2019	7156	5.6	26.9	46.5
Togo	Sep 2018 – Jun 2019	6171	4.9	35.5	53.2

Note: own calculations based on PHMECV data.

Figure A1 Food expenditure shares according to PHMECV



Note: own calculations based on PHMECV data.

Matching PHMECV to WAEMU and WFP food items

To obtain a realistic picture of the development of prices of food groups, we weight the CPI and WFP price information by local consumption preferences from the PHMECV data. To do so, we match food items available in these sources with PHMECV items wherever possible. In the food group's price aggregate, the CPI or WFP item then receives a weight corresponding to the importance of the PHMECV in local consumption.

PHMECV items that cannot be matched with a single item in the CPI and WFP data are matched either with a subset of comparable items (indicated in the table below) or with all items of the foodgroup (which is what happens where there are missing values in the table). In the WFP data, some food items without specific equivalents in the PHMECV items were recorded. These are included when PHMECV items are matched with all WFP items of the food group.

Table A1 Food matching Table

Foodgroup	PHMECV item	WAEMU item	WFP item
Cereals	Riz local Gambiaka	Céréales non transformées	Rice
			Rice (local)
			Rice (ordinary, first quality)
			Rice (ordinary, second quality)
			Rice (paddy)
			Rice (high quality)
	Riz local fumé (malo-woussou)	Céréales non transformées	Rice
			Rice (local)
			Rice (ordinary, first quality)
			Rice (ordinary, second quality)
			Rice (paddy)
			Rice (high quality)
	Riz importé parfumé	Céréales non transformées	Rice (imported)
			Rice (denikassia, imported)
	Riz brisé importé	Céréales non transformées	Rice (imported)
			Rice (denikassia, imported)
	Maïs en épi	Céréales non transformées	Maize
			Maize (local)
			Maize (white)
			Maize (imported)
	Maïs en grain	Céréales non transformées	Maize
			Maize (local)

			Maize (white)
			Maize (imported)
	Mil	Céréales non transformées	Millet
	Sorgho	Céréales non transformées	Sorghum
			Sorghum (white)
			Sorghum (imported)
			Sorghum (red)
			Sorghum (local)
	Blé	Céréales non transformées	Wheat
	Fonio	Céréales non transformées	Fonio
	Autres céréales	Céréales non transformées	
	Farine de maïs	Farines, semoules et gruaux	Cornstarch
	Farine de mil	Farines, semoules et gruaux	
	Farine de blé local ou importé	Farines, semoules et gruaux	Wheat flour
			Wheat flour (imported)
	Autres farines de céréales	Farines, semoules et gruaux	
	Pâtes alimentaires	Pâtes alimentaires	Pasta (spaghetti)
			Pasta (macaroni)
	Pain moderne	Pains	Bread
	Pain traditionnel	Pains	Bread
	Farines de manioc	Autres produits à base de tubercules et de plantain	Cassava flour
			Couscous
			Semolina
Roots	Manioc	Tubercules et plantain	Cassava
			Cassava (fresh)
			Cassava (cossette)
	Igname	Tubercules et plantain	Yam
			Yam (white)
			Yam (florido)
			Yam (dry)
			Yam (yellow)
	Pomme de terre	Tubercules et plantain	Potatoes
			Potatoes (red)
	Taro, macabo	Tubercules et plantain	Taro
	Patate douce	Tubercules et plantain	Sweet potatoes
	Autres tubercules n.d.a.	Tubercules et plantain	
	Gari, tapioca	Autres produits à base de tubercules et de plantain	Cassava meal (gari)
			Cassava meal (gari, fine)
			Cassava meal (tapioca)
	Attiéke	Autres produits à base de tubercules et de plantain	Cassava meal (attieke)
			Yam (flour)
Pulses	Haricot vert	Légumes frais en fruits ou racine	Beans (haricot)
	Petits pois	Fruits secs et noix	
	Petit pois secs	Fruits secs et noix	Peas (green, dry)
	Niébé/Haricots secs	Légumes secs et oleagineux	Beans (niebe)

			Beans
			Beans (white)
			Beans (red)
			Beans (black)
	Arachides fraîches en coques	Légumes secs et oleagineux	Groundnuts (shelled)
			Groundnuts
			Peanut
	Arachides séchées en coques	Légumes secs et oleagineux	Groundnuts (shelled)
			Groundnuts
			Peanut
	Arachides décortiquées ou pilées	Légumes secs et oleagineux	Groundnuts (unshelled)
			Groundnuts
			Peanut
	Arachide grillée	Légumes secs et oleagineux	Groundnuts
			Groundnuts (small, unshelled)
			Peanut
	Pâte d'arachide	Légumes secs et oleagineux	Groundnuts (paste)
	Sésame	Légumes secs et oleagineux	
			Soybeans
			Groundnuts (Bambara)
Fish, meat, eggs	Viande de bœuf	Boeuf	Meat (beef)
			Meat (beef, second quality)
			Meat (beef, without bones)
	Viande de chameau	Boeuf	
		Porc	
		Mouton - chèvre	
	Viande de mouton	Mouton - chèvre	Meat (mutton)
			Meat (sheep)
			Meat (sheep, second quality)
	Viande de chèvre	Mouton - chèvre	Meat (goat)
	Abats et tripes (foie, rognon, etc.)	Charcuterie et conserves, autres viandes et préparations à base de viande	
	Viande de porc	Porc	Meat (pork, first quality)
			Meat (pork, second quality)
	Poulet sur pied	Volaille	Meat (chicken, local)
	Viande de poulet	Volaille	Meat (chicken, local)
			Meat (chicken, frozen, imported)
	Viande d'autres volailles domestiques	Volaille	
	Charcuterie (jambon, saucisson), conserves de viandes	Charcuterie et conserves, autres viandes et préparations à base de viande	
	Gibiers	Porc	
		Volaille	
		Mouton - chèvre	
		Boeuf	

	Autres viandes n.d.a.	Charcuterie et conserves, autres viandes et préparations à base de viande	
	Poisson frais type 1	Poissons frais	Fish (fresh)
			Fish (appolo)
			Fish (tilapia)
			Fish (fresh, silvi)
			Fish (goldstripe sardinella)
			Fish (barbel, sole)
			Fish (mullet, catfish)
			Fish (goldstripe sardinella)
	Poisson frais type 2	Poissons frais	Fish (fresh)
			Fish (appolo)
			Fish (tilapia)
			Fish (fresh, silvi)
			Fish (goldstripe sardinella)
			Fish (barbel, sole)
			Fish (mullet, catfish)
			Fish (goldstripe sardinella)
	Poisson frais type 3	Poissons frais	Fish (fresh)
			Fish (appolo)
			Fish (tilapia)
			Fish (fresh, silvi)
			Fish (goldstripe sardinella)
			Fish (barbel, sole)
			Fish (mullet, catfish)
			Fish (goldstripe sardinella)
	Poisson frais type 4	Poissons frais	Fish (fresh)
			Fish (appolo)
			Fish (tilapia)
			Fish (fresh, silvi)
			Fish (goldstripe sardinella)
			Fish (barbel, sole)
			Fish (mullet, catfish)
			Fish (goldstripe sardinella)
	Poisson fumé type 1	Poissons et autres produits séchés ou fumés	Fish (smoked)
	Poisson fumé type 2	Poissons et autres produits séchés ou fumés	Fish (smoked)
	Poisson séché	Poissons et autres produits séchés ou fumés	Fish (dry)
	Crabes, crevettes et autres fruits de mer	Autres produits frais de mer ou de fleuve	Shrimps
	Conserves de poisson	Autres conserves de poissons	
	Œufs	Oeufs	Eggs
			Snail
Vegetables	Salade (laitue)	Légumes frais en feuilles	Lettuce
	Choux	Légumes frais en feuilles	Cabbage
	Carotte	Légumes frais en fruits ou racine	Carrots
	Concombre	Légumes frais en fruits ou racine	Cucumbers

	Aubergine, Courge/Courgette	Légumes frais en fruits ou racine	
	Poivron frais	Légumes frais en fruits ou racine	
	Tomate fraîche	Légumes frais en fruits ou racine	Tomatoes
	Tomate séchée	Légumes secs et oleagineux	
	Gombo frais	Légumes frais en fruits ou racine	Okra (fresh)
	Gombo sec	Légumes secs et oleagineux	
	Oignon frais	Légumes frais en fruits ou racine	Onions
			Onions (shallot)
	Ail	Légumes frais en fruits ou racine	
	Feuilles locales 1	Légumes frais en feuilles	Cassava leaves
			Potato Leaves
	Feuilles locales 2	Légumes frais en feuilles	Cassava leaves
			Potato Leaves
	Feuilles locales 3	Légumes frais en feuilles	Cassava leaves
			Potato Leaves
	Feuilles locales 4	Légumes frais en feuilles	Cassava leaves
			Potato Leaves
	Autres légumes en feuilles	Légumes frais en feuilles	Leafy vegetables
	Autre légumes frais n.d.a.	Légumes frais en fruits ou racine	
	Concentré de tomate	Légumes frais en fruits ou racine	Tomatoes (paste)
	Autres légumes secs n.d.a.	Légumes secs et oleagineux	
Fruits	Mangue	Autres fruits frais	Mangoes
	Ananas	Agrumes	
	Orange	Agrumes	Oranges
	Banane douce	Autres fruits frais	Bananas
			Bananas (local)
			Bananas (imported)
	Citrons	Agrumes	Lemons
	Autres agrumes	Agrumes	
	Avocats	Autres fruits frais	
	Pastèque, Melon	Autres fruits frais	
	Dattes	Fruits secs et noix	
	Noix de coco	Fruits secs et noix	Coconut (dried)
	Autres fruits (pommes, raisin, etc.)	Autres fruits frais	
		Fruits secs et noix	
	Noix de cajou	Fruits secs et noix	Cashew nut
	Noix de karité	Fruits secs et noix	
	Plantain	Tubercules et plantain	Plantains
	Noix de cola	Fruits secs et noix	
			Papaya
			Cashew fruit
Fats	Beurre	Beurre, margarine	
	Beurre de karité	Autres matières grasses	
	Huile de palme rouge	Huiles	Oil (palm)
			Oil (palm nut)

	Huile d'arachide	Huiles	Oil (groundnut)
	Huile de coton	Huiles	
	Huile de palme raffinée	Huiles	Oil (palm) Oil (palm nut)
	Autres huiles n.d.a. (maïs, soja, huile palmiste, etc.)	Huiles	
	Soumbala (moutarde africaine)	Sel, épices, sauces et produits alimentaires n.d.a	
	Mayonnaise	Autres matières grasses	
			Oil (vegetable)
			Oil (vegetable, imported)
Dairy	Lait frais	Lait	Milk (cow, fresh)
	Lait caillé, yaourt	Lait	
	Lait concentré sucré	Lait	
	Lait concentré non-sucré	Lait	
	Lait en poudre	Produits laitiers	Milk (powder)
	Fromage	Produits laitiers	
	Lait et farines pour bébé	Laits infantiles et farines lactees pour bebe	
	Autres produits laitiers	Produits laitiers	
Sweets, sugar, salt	Croissants	Pâtisseries, gâteaux, biscuits, vienoiseries	
	Biscuits	Pâtisseries, gâteaux, biscuits, vienoiseries	
	Gâteaux	Pâtisseries, gâteaux, biscuits, vienoiseries	
	Beignets, galettes	Pâtisseries, gâteaux, biscuits, vienoiseries	
	Canne à sucre	Autres fruits frais	
	Sucre (poudre ou morceaux)	Sucre	Sugar
	Miel	Confiture, miel, chocolat et confiserie	
	Chocolat à croquer, pâte à tartiner	Confiture, miel, chocolat et confiserie	
	Caramel, bonbons, confiseries, etc.	Confiture, miel, chocolat et confiserie	
	Sel	Sel, épices, sauces et produits alimentaires n.d.a	Salt
	Chocolat en poudre	Café, thé, cacao et autres végétaux pour tisanes	
Beverages, other	Piment	Sel, épices, sauces et produits alimentaires n.d.a	Peppers (red, dry)
	Gingembre	Sel, épices, sauces et produits alimentaires n.d.a	
	Cube alimentaire (Maggi, Jumbo,)	Sel, épices, sauces et produits alimentaires n.d.a	
	Arôme (Maggi, Jumbo, etc.)	Sel, épices, sauces et produits alimentaires n.d.a	
	Vinaigre /moutarde	Sel, épices, sauces et produits alimentaires n.d.a	
	Autres condiments (poivre etc.)	Sel, épices, sauces et produits alimentaires n.d.a	
	Autres produits alimentaires	[all WAEMU food items]	
	Café	Café, thé, cacao et autres végétaux pour tisanes	Coffee
	Thé	Café, thé, cacao et autres végétaux pour tisanes	
	Autres tisanes et infusions n.d.a. (quinquelibat, citronelle, etc.)	Café, thé, cacao et autres végétaux pour tisanes	
	Jus de fruits (orange, bissap, gingembre, jus de cajou,etc.)	Autres fruits frais Boissons non alcoolisées artisanales Agrumes	
	Eau minérale/ filtrée	Boissons non alcoolisées industrielles	
	Boissons gazeuses (coca, etc.)	Boissons non alcoolisées industrielles	

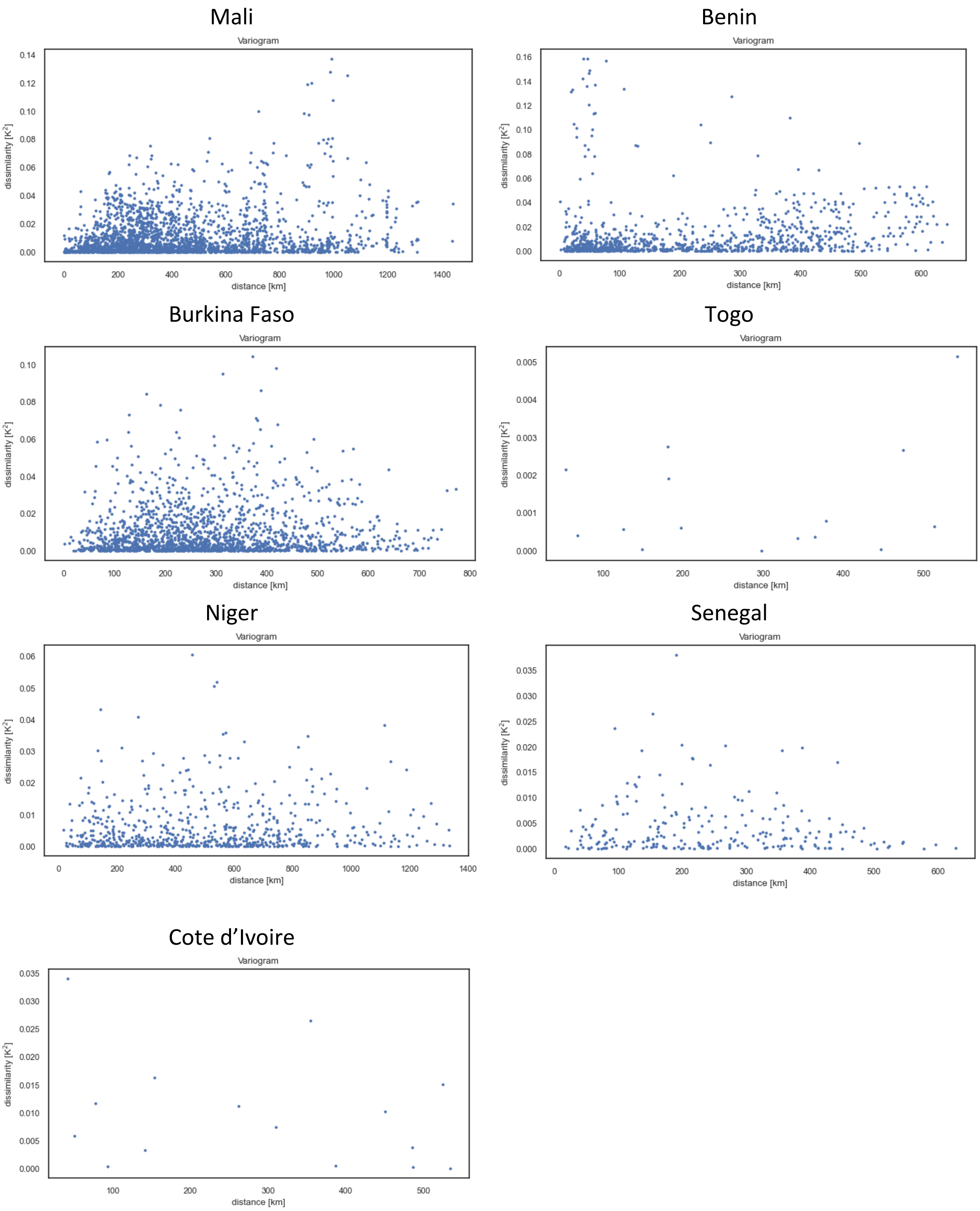
	Jus en poudre	Boissons non alcoolisées industrielles	
	Bières et vins traditionnels (dolo, vin de palme, vin de raphia, etc.)	Boissons non alcoolisées artisanales	
	Bières industrielles	Boissons non alcoolisées industrielles	
			Cocoa

Table A3 Price changes between April and August 2020

Food Group	Benin	Burkina Faso	Côte d'Ivoire	Mali	Niger	Senegal	Togo
Cereals	10.0	7.3	9.3	7.8	18.2	0.9	10.6
Roots	7.7	41.3	7.7	37.9	19.0	33.7	11.2
Pulses	-1.1	8.4	-1.5	8.3	-3.7	7.1	-0.3
Fish, meat, eggs	6.6	3.0	7.2	4.2	5.4	3.2	-5.3
Vegetables	-21.1	33.1	-23.5	56.8	45.0	47.6	-15.8
Fruits	-30.8	1.3	-12.4	7.1	-18.1	14.2	-17.4
Fats	1.7	0.1	1.5	-1.2	-2.1	0.2	-4.9
Dairy	-0.4	0.0	0.3	-0.1	0.0	-0.3	-0.8
Sweets, sugar, salt	-10.2	1.1	0.6	-0.8	-5.5	-0.3	-2.1
Beverages, other	-11.9	5.7	-13.0	15.6	19.8	14.5	-5.8

Notes: Percentage point difference in price level from April to August 2020 according to country-level CPI data.

Figure A1 Dissimilarity in cereal price changes (April and August 2020) between market pairs



Note: The y-axis shows the dissimilarity in cereal price changes between April and August 2020 between all market pair combination in a country. The x-axis shows the distance between market pairs.

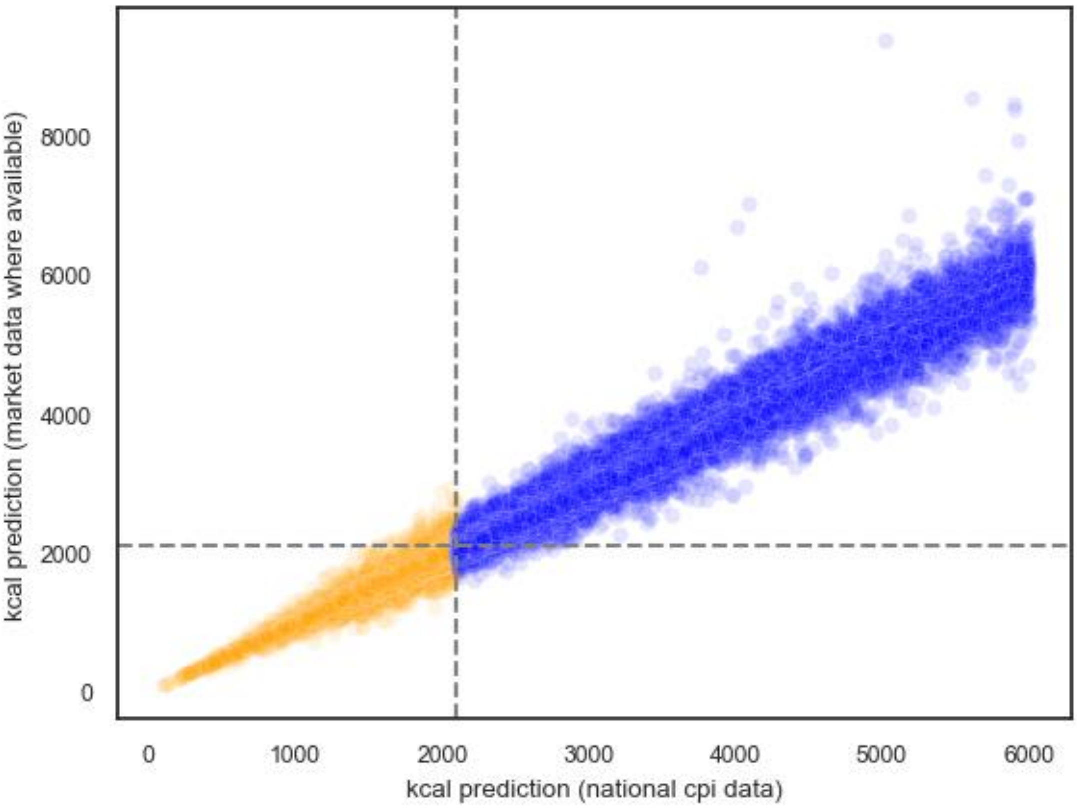
Table A4 Compensated (own) price elasticities by country and total expenditure

	ML	N	BF	CI	TG	SEN
Cereals	-1.094	-0.694	-1.069	-1.582	-1.544	-1.023
	-0,077	-0,139	-0,074	-0,09	-0,104	-0,076
Roots	-1.009	-1.108	-1.173	-1.084	-0.999	-0.998
	-0,09	-0,12	-0,084	-0,088	-0,076	-0,084
Pulses	-1.269	-1.083	-1.776	-1.573	-1.158	-1.047
	-0,137	-0,174	-0,229	-0,136	-0,127	-0,121
Fish, meat, eggs	-0.771	-0.748	-0.869	-0.780	-0.378	-0.432
	-0,079	-0,068	-0,158	-0,078	-0,058	-0,102
Vegetables	-0.856	-1.483	-0.899	-1.007	-0.777	-0.813
	-0,064	-0,104	-0,075	-0,053	-0,062	-0,064
Fruits	-1.197	-0.845	-1.232	-1.121	-0.957	-1.102
	-0,072	-0,062	-0,124	-0,073	-0,124	-0,105
Fats	-0.605	-0.576	-1.068	-1.185	-1.064	-1.141
	-0,12	-0,078	-0,147	-0,124	-0,139	-0,148
Dairy	-1.121	-0.689	-0.950	-1.745	-1.176	-1.364
	-0,068	-0,08	-0,07	-0,234	-0,067	-0,152
Sweets, sugar, salt	-1.116	-0.670	-0.832	-0.600	-0.581	-0.419
	-0,07	-0,176	-0,09	-0,117	-0,079	-0,114
Beverages, other	-0.864	-0.809	-0.870	-0.945	-0.901	-1.158
	-0,061	-0,042	-0,076	-0,027	-0,042	-0,066

Note: Elasticity calculated based on QUAIDS demand system and PHMECV data. Demographic control variables include household size, rural, sex of household head, share women, dependency ratio, household head is literate, household has access to drinking water in the dry season, access to electricity. Standard errors below row with elasticity estimates.

Figure A4 Predicted calorie intake in August 2020 with CPI versus market prices

(using all food groups available at market level)



	MLI	NER	BFA	CIV	SEN	TGO	BEN
Food Poverty (CPI)	0.18	0.24	0.32	0.33	0.18	0.35	0.19
Food Poverty (cereal market)	0.17	0.25	0.33	0.31	0.21	0.36	0.2
Exclusion Error	0.06	0.03	0.02	0.09	0.00	0.01	0.04
Inclusion Error	0.01	0.03	0.03	0.00	0.03	0.01	0.03

Notes: Results based on predicted calorie consumption and a food poverty threshold of 2100 kcal. For better visibility, kcal values above 6000 are not shown in the scatter plot. Inclusion and exclusion errors refer to number of individuals predicted non-poor and poor respectively with benchmark model but poor and non-poor respectively with model that used market level cereal prices.

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