How does information on minimum and maximum food prices affect measured monetary poverty?

Evidence from Niger[1]

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Abstract

Do households facing different realizations of prices rather than a simple price alter the results of poverty analyses? To address this question, we exploit a unique dataset from Niger in which agropastoral households provide the observed *minimum and maximum prices* they paid for each consumed product in each season. We estimate poverty measures based on this price information using several absolute poverty line methodologies. Prices are used for valuing household consumption bundles, estimating household-specific price indices, valuing minimal calorie requirements, and extrapolating the link between food poverty and consumption.

The results for Niger show statistically significant differences in the estimated chronic and dynamic poverties for these approaches, especially for international poverty comparisons and seasonal transient poverty monitoring. Specifically, using minimum and maximum prices generates gaps in the estimated poverty rates for Nigerien agropastoral households that exceed regional poverty disparities, which implies that regional targeting priorities in poverty alleviation policies would be reversed if these alternative prices are utilized.

This result suggests that typically estimated poverty statistics, which assume that each household, or even cluster, faces a unique price for each product in a given period, may be less accurate for policy monitoring than generally believed.

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1. Introduction

Price deflation is a major component of analyzing living standards and poverty in developing economies and elsewhere. This is notably the case in countries for which the spatial and time price differences that households face can be substantial. In this context, pioneering authors[2] stressed that accounting for price differences is essential for assessing deprivation and wealth, especially for poor individuals. Price discrepancies are typically corrected by dividing household income or household total consumption by price indices. In this work, we examine an issue that has been much overlooked in the literature: the fact that any given household can face, in addition to the abovementioned discrepancy, different realizations of prices for the same product in the same period instead of a unique price. Does this change the perspective of poverty analyses?

Spatial and time price differences have been scrutinized in the literature. By focusing on price differences in Rwanda for several seasons, Muller (2002) identifies substantial spatial price differences and price discrimination faced by poor individuals, even in a small rural country. Poor individuals may sometimes live in remote areas that are distant from marketplaces and hence pay higher prices. As an alternative, poor individuals may consume lower quality products, thereby be appearing to pay lower prices in data insufficiently accounting for parities. In other contexts, mainly for urban areas, only small spatial differences in price were found (Musgrove and Galindo, 1988; Gibson and Kim, 2013), which

[2] Such as Sen (1981), Pinstrup-Andersen (1985) and Stern (1989).

suggests that examining diverse contexts, and not just the US that dominate price studies literature, is useful.

However, Muller (2005) shows that when there is a weak association between prices and nominal living standards, price dispersion should be globally beneficial to social welfare, thanks to the functional shape of the price deflation in the formula of living standard indicators. Therefore, neutral price dispersion across households could reduce aggregate poverty. A consequence of these conflicting mechanisms is that the effect of price corrections on poverty is theoretically ambiguous and is an issue that should be empirically studied.

Deflation has been found to be crucial in estimating poverty lines and poverty indicators, and special attention has been devoted to rural-urban price gaps[3]. Purchasing power parities within countries have been particularly studied in large countries[4] and found to substantially influence poverty assessments. Even for smaller countries, precise spatial deflators have been found to matter for poverty analyses (e.g., in Vietnam, Gibson et al. 2016). Typically, in these absolute poverty studies, food Engel curve adjustments are used to convert a minimal calorie requirement into a poverty line level that can be compared to household total consumption expenditure or incomes in distinct places or periods, which raises the question of how price data affect the estimation of poverty statistics, even when this poverty line estimation method is utilized. Failing to accurately correct for price dispersion generally leads to biased estimates of chronic and transient

[3] See Black (1952), Ravallion and Bidani (1994) and Rao (2000).

[4] E.g., studies conducted in India and China by Deaton and Dupriez (2011), Majumder et al. (2012), Li and Gibson (2014).

poverty. For example, sizable biases have been found to emerge from seasonal and geographical price gaps across households in Rwanda (Muller, 2008).

Unfortunately, accurate seasonal and local price information is rarely available. However, when such price information can be obtained, it can be used to improve poverty alleviation policies, for example, by promoting the development of focused antipoverty transfer schemes, such as those first introduced by Muller and Bibi (2010) for Tunisia, with living standards deflated by estimated true price indices. In that case, more precise price information enhanced the targeting efficiency of social policies and reduced the need for social funds.

One issue that arises when considering price correction in poverty analysis is that a household may pay different prices for the same product in the same period. These differences, faced separately by each individual, may correspond to differences in the quality of the products, which may or may not be taken into account by the estimation methods used. These 'individual-specific' differences may also emerge from the social relationship that exists between buyers and sellers that incite some individuals to adjust the asked or given price to the benefit or detriment of their transaction partner. Furthermore, prices can vary with the timing of the transaction during the market day, as sellers are more willing to offer bargains at the closing time of the market. In addition, buyers and sellers may learn about prices during the day, and they may even make mistakes. Prices may also vary with days, reflecting high frequency variations in supply and demand conditions. Other transaction costs, such as those related to bulk purchases, transport, packaging costs, or purchases on distinct days, may contribute to idiosyncratic price dispersion. These individual-specific price differences may also be generated by other unobserved reasons. In all these cases, rather than facing a unique price for a given product at a given time, each household faces diverse realizations of prices drawn from some probability distribution, empirically bounded by a minimum price and a maximum price. Significant variations in the mean prices paid by different buyers, and even the same buyer, have been found in studies of specific markets, such as the Marseille fish market, suggesting that the notion of a unique price may sometimes be misleading (Kirman, 2010, Chapter 3).

In developing countries, for which market price data are rarely available, observations of unit values are often used to proxy prices. The unit value is calculated as the ratio of value over quantity for a given good, using records of purchases of this good obtained from a household survey. Sophisticated estimation methods, for example, those used for demand systems, have been developed to account for household choices of varieties, often of different qualities, involved in the unit value data, particularly the method proposed by Deaton (1987, 1988).[5] In Indonesia, using data on both unit value and price, McKelvey (2011) find substantial quality substitution. However, Deaton and Dupriez (2011) do not refrain from using unit values data for analyzing poverty in Brazil, India and China. These methods typically use spatial location to identify price variability, which may be a strong assumption if there are local, and even individual, dispersions in prices. In that case, purging the quality choice by households may disregard some information about the price dispersion that each given household may face.

[5] See also Deaton (1990, 1997), Crawford, Laisney and Preston (2003), and Ayadi et al (2003).

Does this residual price dispersion, possibly occurring for each individual separately, regardless of its source : quality, choice, social relations, transactions constraints or mere randomness, affect poverty measurement? The aim of this study is to investigate this question in agropastoral households in Niger. Using alternative information, observed maximum and minimum food prices, may potentially generate a substantial interval of (partially identified) poverty estimates. To the best of our knowledge, this is the first time these issues have been assessed using precise economic and statistical methods.

Our study is based on a unique dataset on Niger that includes information provided by agropastoral households regarding the observed lowest and highest prices they have paid for each food product that they purchased, for each of the three seasons of the year. Using these data, we estimate poverty by considering three alternative poverty lines (and three associated deflated living standard variables): This study employs the World Bank international poverty line of 1.90 purchasing power parity (PPP) US $ a day, an absolute poverty line based on a minimal calorie requirement and minimum prices, and a similar poverty line based on maximum prices. Using the 1.90 dollar a day poverty line allows this study to consider a complementary perspective of how international poverty lines that mostly account for country price differences perform when compared to more precise cost-of-basic-needs methods that account for within-country price differences and here even account for different realizations of prices faced by individuals. All these variants are extended to chronic and transient poverty measures across seasons.

Our results exhibit statistically significant differences in poverty levels when they are measured with these three approaches. The gaps found in poverty that are caused by using the observed minimum prices instead of maximum prices are considerable when considering the international poverty line that is typically used for international poverty comparisons. These gaps are also substantial when considering seasonal transient poverty, even when using the estimated absolute poverty lines based on basic nutritional needs. In that case, the impact of using one type of price rather than the other is small when considering annual or chronic poverty. However, these changes remain large enough to reverse the North vs South targeting priority in poverty alleviation policies that are derived from estimated poverty profiles.

The rest of the paper is organized as follows. In Section 2, we present the context of Niger and the data used. Section 3 discusses the methods used to compute the poverty indices. Section 4 reports the estimation results. Finally, Section 5 presents the conclusion.

2. Context and Data

Niger is a large landlocked country and in 2014, the population was 17 million. The country's economy is essentially based on agriculture (40 percent of the GDP), with a large contribution from the livestock sector (11 percent of the GDP; Ministère de l'Elevage, 2016). In fact, the livestock sector is a mainstay of the country's economy, since 87 percent of the population is involved in this sector as a primary or secondary activity. Moreover, the income of 10 percent of rural households and up to 43 percent of households in pastoral zones directly come from livestock.

In a survey conducted in 2011 by the National Institute of Statistics in Niger on living standards and agriculture, 77 percent of the 4,000 households interviewed raised livestock as a source of income or to compensate for low agricultural income. However, agropastoral households are far from being the poorest individuals in Niger, as noted, for example, in Gueye et al. (2008). In particular, agropastoral households have generally been able to preserve at least part of their animal capital, sometimes over several drought periods.

The data used in this study were obtained from a specialized survey collected by the Ministry of Livestock in Niger. This survey was conducted in the framework of two development projects in Niger: the "PRAPS: Projet Régional D'appui au Pastoralism au Sahel" and the "PASEL: Programme d'Appui au Secteur de l'Elevage". We were able to access data obtained during the first round of this survey, which was conducted in October 2016 and is the only round useful for our purpose. It is a two-stage sample survey which covered all seven regions of the country. A pre-survey was conducted with the aim of stratifying agropastoral-households according to the size of their herd (small, medium and large). The sampling frame of the first stage is based on the 2012 national directory of localities. There was no regional stratification at the first stage of sampling . In this first stage, ninety villages were first selected with probabilities proportional to their actual size. Then, within each of these villages, pastoral and agropastoral households were assigned to one of three strata pre-defined during the pre-survey. Then in each stratum households were randomly drawn proportionally to the strata size.

The sample is truncated to eliminate urban and peri-urban households that are not part of our population of interest: true pastoral and agropastoral households. The excluded households were often too rich to be included in estimations of nutrient subsistence minima and consumption habits of poor individuals. Most excluded households did not produce milk and live in urban communes in the Dosso region. We controlled for peri-urban characteristics and then verified that this truncation step, which removes only 3 localities, did not significantly affect the balance of the sample across regions or number of cattle owned.

After cleaning the data and removing obvious outliers in terms of household caloric consumption, total expenditures, and food prices, we obtained a total of 671 observations. Our sample is for more than 85 percent composed of households that owned cattle and sheep. The Online Appendix provides details on how all these variables were calculated.

The surveyed households provided information about their sociodemographic characteristics, budgets, food consumption, agropastoral activities, and crucially, the observed minimum and maximum prices they faced for each food product in each season. Specifically, to obtain the minimum price paid by a household during a given season s for a given product p, the following question was asked: "*During season s, what is the lowest price at which you bought product p?*". For the maximum price, the corresponding question was: "*During season s, what is the highest price at which you bought product p*?". Admittedly, these questions seem to require an difficult memory task, as often in consumption surveys based on retrospective questions. However, there are reasons to suggest that respondents may have had the ability to carry out this task in conditions that prevent these data to be uninformative. First, minimum and maximum extreme prices, which are related to more salient events than any usual transaction, may be easier to remember than the prices of some unnoticeable past transaction. Second, severe omissions in this survey should materialize through measured consumption levels that would drastically collapse over time when gradually considering more ancient seasons. The density graphs in Section 9 in the online appendix show that this is not substantially the case, whether using the observed minimum prices or the observed maximum prices. The same conclusion applies to the bottoms of the distributions, which may be more relevant for poverty. Finally, in Africa, national poverty statistics often rely on consumption data collected retrospectively, despite the findings in Tanzania in Beegle et al. (2012) that personal diaries perform better. So, it is does not seem unfit to examine a similar approach to produce statements about official statistics. The collected price[6] information may reflect the instability of prices during some periods when they varied every day or each week. This detailed information on the food prices faced by each household enables us to compute households' food expenditure and individual price indices using alternatively the minimum and maximum prices collected at the household level. However, the mean and median prices cannot be computed for each household from these data.

The estimate of the caloric price for calculating the food poverty line also depends on whether minimum prices or maximum prices are considered. Moreover, as we discuss later, the extrapolation step in the estimation of the absolute poverty line,

[6] The survey collected information on the prices paid by households in the market rather than unit value.

which is driven by a food Engel curve estimation, may generate an additional gap in the poverty statistics, notably when prices are included in the Engel curve equation.

Finally, we construct the price and living standard indicators not only at the year level, as is customary for poverty statistics, but also separately for three distinct seasons. This added step mitigates the cases of observed minimum and maximum prices for the same product that would correspond to distinct prices measured over long time periods.

By convention, the questionnaire distinguishes three seasons. The hot and dry season lasts from March to June, the rainy season begins in July and ends in October, and the cold and dry season lasts from November to February. Most harvests take place between October and December. Of course, these patterns only basically fit the diverse local circumstances in a large country.

The hot and dry season and the rainy season are lean seasons for agropastoral households. The hot and dry season negatively affects livestock activity, while the rainy season is a planting period in which households generally have no cereal stocks. During the hot and dry season, agropastoral households are confronted with a lack of pasture and water for their animals, resulting in weight loss and lower market value. However, four-fifths of the total consumption of these households is still food during this time of the year.

In the rainy season, agropastoral households work on their fields, and they progressively exhaust their cereal stock. Moreover, even if the first rains in this season benefit the animals, some of the abovementioned negative effects of the hot and dry season may persist in the rainy season. The market value of animals may not be sufficient to buy enough cereals, which are costly in that period. Food accounts for 87 percent of total consumption and almost as much as 86 percent in the cold and dry season. The strong seasonality of food prices has been well acknowledged, particularly for millet, for which recurrent price spikes have been studied (Araujo-Bonjean and Simonet, 2016).

3. Food Expenditure and Food Prices

As in most consumption surveys, price information was occasionally missing for some products and some households. In that case, we applied an imputation algorithm to replace these data with the median values of the prices observed in the nearest upper geographical level (see the Online Appendix for details).

Moreover, for some households and some products, the stated minimum and maximum prices are identical. Table 1 indicates the proportions of these households for each product used to construct the price index and by season. The proportions range from 1 percent (cowpea in the hot and dry season) to 60 percent (tobacco) percent depending on the product and season. Although these proportions are high for some products in some seasons, it is fair to say that overall, and for a high proportion of households, the stated minimum and maximum prices differ for all seasons. During the cold and dry season, for ten of these products, more than one-third of households stated a unique price; this is the case for seven products in the hot and dry season but only five products in the rainy season. Additionally, these data do not obviously suggest that the differences between the minimum and maximum prices arise from quality differences. For example, the hedonic OLS regressions of log price indices respectively based on the observed minimum and maximum price on households' socio-demographic characteristics and location types, and that include village fixed effects, show generally insignificant estimation of the coefficients, except for season dummies and locality fixed effects. This is not what would be expected if household preferences would incite them to choose different qualities, or whether different location types would offer different qualities of the consumed products. The same patterns (not shown) of insignificant effects of socio-demographic characteristics and location types, occurs when regressing the log prices of each individual products[7]. The only exception are the prices of condiments (negative effects of the dummies for the Fulani and village) and oil (negative effect of village, positive effect of household size), and perhaps fresh milk (negative effect of the Haoussa dummy) and especially sugar (negative effect for the dummies of the Haoussa, the Fulani and the Tuareg). Finally, household price dispersion is supported by the results of a survey conducted by the Institut National de la Statistique (2015), showing that in eight[8] regions of the country, the respondents greatly vary in terms of their assessments of changes in the price of cereals. These responses are hard to reconcile with the common belief that a unique price exists, at least at the village level. Under these conditions, clearly, the issue of individual-specific price dispersion that has been overlooked thus far should be taken seriously.

[7] The only exceptions are for relatively margin products: the prices of condiments (negative effects of the dummies if the Fulani and village) and oil (negative effect of village, positive effect of household size), and perhaps fresh milk (negative effect of the Haoussa dummy) and especially sugar (negative effect of the dummies of the Haoussa, the Fulani and the Tuareg).

[8] Seven regions (Agadez, Diffa, Dosso, Maradi, Tahoua, Tilabéri, and Zinder) plus Niamey, the capital.

Table 1: Percentage of Households with Identical Observed Minimum and Maximum Prices

Products	Cold and dry season	Hot and dry season	Rainy season
Millet	26.53	16.39	8.94
Sorghum	17.88	19.67	6.26
Cowpea	31.15	1.04	2.53
Maize	49.18	14.75	25.19
Groundnut	30.25	49.03	71.39
Butter	59.17	59.02	42.32
Kola nut	23.40	11.17	9.24
Okra	7.45	25.48	25.63
Oil	33.83	28.02	21.01
Fresh milk	42.92	42.62	30.10
Curdled milk	15.05	48.29	15.35
Bread	41.13	41.13	41.13
Edible pasta	24.74	25.04	7.15
Fish	42.03	42.03	42.03
Sugar	15.80	14.61	27.27
Tobacco	36.36	59.91	21.76
Tea	17.59	9.69	9.99
Condiments	34.28	33.68	23.99
Meat	27.42	28.46	21.61
Poultry	23.25	4.92	23.85

The seasonal means of the observed minimum and the observed maximum price values are presented in Table 2. The mean gap between the observed minimum price and the observed maximum price, in the 'Diff' columns, greatly varies across products and across seasons. For most products and seasons, this gap is significant. In the cold and dry season, for 8 of 20 products, the gap exceeds 100 CFA per kg or per liter; this also occurs for 11 products in the hot and dry season and 12 products in the rainy season that satisfy the same conditions. Broadly, the products with the greatest relative gaps between the observed minimum and maximum prices are sorghum, okra, cowpea, fresh and curdled milk, fish, tobacco, meat, and poultry. In contrast, maize, butter, and kola are products with the smallest gaps. Moreover, for some products, this gap greatly varies across seasons, while for others, even when the gap is large, it is stable across seasons, as for meat. For millet or maize, the gap can change by three or four times from one season to another (e.g. the millet price ranges from 15 CFA/kg in the cold dry season to 54 CFA/kg in the rainy season). Note that in the studied context, there is only one variety present for some food product, at least for millet, sorghum and maize. It is therefore implausible that the observed price gap for these products would be originated from substantial quality differences.

Table 2: Mean Seasonal Prices (CFA)

Products	Cold and dry season				Hot and dry season				Rainy season			
	N	Pmax	Pmin	Diff	N	Pmax	Pmin	Diff	N	Pmax	Pmin	Diff
Millet (kg)	671	246.4 (.639)	230.5 (.643)	15.9 (.907)	671	239.1 (.310)	211.7 (.080)	27.4 (.320)	671	268 (.545)	213.3 (.076)	54.7 (.550)
Sorghum (kg)	671	187 (.080)	163.8 (.069)	23.2 (.105)	671	227.9 (.383)	208.9 (.383)	19 (.542)	671	230.3 (.077)	210.1 (.068)	20.3 (.103)
Cowpea (kg)	671	342 (.289)	309.8 (.256)	32.2 (.387)	671	361.8 (.416)	318.6 (.259)	43.2 (.491)	671	378.9 (.234)	333.3 (.196)	45.6 (.306)
Maize (kg)	559	197.6 (.083)	188 (.068)	9.6 (.108)	671	244.6 (.161)	227.5 (.079)	17.1 (.180)	559	242.2 (.324)	217 (.078)	25.2 (.334)
Groundnut (kg)	470	440.5 (.290)	390.9 (.286)	49.6 (.408)	470	472.9 (.161)	383.4 (.200)	89.5 (.257)	470	604.5 (1.21)	470.5 (.245)	134 (1.23)
Butter (kg)	402	1301.4 (.714)	1024.2 (.377)	277.3 (.807)	275	1563.9 (1.37)	1157 (.755)	406.9 (1.57)	387	1309.8 (.936)	1002.9 (.908)	306.6 (1.30)
Kola nut (kg)	630	561.2 (2.36)	506.7 (2.25)	54.4 (3.27)	630	501.1 (1.90)	377.5 (1.45)	123.6 (2.39)	630	590.6 (2.35)	451.3 (1.80)	139.2 (2.96)
Okra (kg)	630	967.5 (1.03)	781.5 (.89)	185.9 (1.37)	630	1075.7 (1.27)	938.7 (1.07)	136.9 (1.66)	503	1161 (1.88)	984 (1.58)	177 (2.46)
Oil (l)	671	869.6 (.641)	802.6 (.466)	67.1 (.792)	671	882.5 (1.23)	779.2 (.477)	103.2 (1.32)	671	902.6 (.908)	803.8 (.469)	98.8 (1.02)
Fresh milk (l)	514	362.3 (.470)	288.9 (.202)	73.4 (.512)	514	455.1 (.348)	334.8 (.278)	120.3 (.446)	597	417.1 (.273)	296.5 (.177)	120.7 (.325)
Curdled milk (l)	630	312.5 (.941)	235.8 (.647)	76.7 (1.14)	597	373.71 (2.28)	343.1 (2.28)	30.6 (3.23)	630	453 (4.48)	310.5 (2.26)	142.4 (5.02)
Bread (kg)	630	350.8 (.330)	304.9 (.311)	45.9 (.453)	630	394.5 (.510)	342 (.485)	52.5 (.704)	630	378.6 (.464)	331.4 (.404)	47.3 (.615)
Pasta (kg)	671	520.8 (.369)	467.1 (.318)	53.7 (.487)	671	522.4 (.371)	468.8 (.319)	53.6 (.489)	671	526.3 (.359)	469.4 (.320)	56.9 (.481)
Fish (kg)	559	1299.5 (1.69)	1080.6 (1.45)	218.9 (2.23)	559	917.1 (1.45)	774.2 (1.14)	142.9 (1.85)	518	1306.4 (2.15)	1110.7 (1.87)	195.7 (2.85)
Sugar (kg)	671	617.8 (.472)	555.7 (.428)	62.1 (.637)	671	602.5 (.456)	541.1 (.420)	61.4 (.620)	671	632.1 (.625)	570.9 (.414)	61.2 (.750)
Tobacco (kg)	638	2012.9 (3.54)	1665.8 (2.60)	347.1 (4.40)	638	1971.7 (3.37)	1767.4 (2.50)	204.3 (4.20)	638	2994.6 (5.71)	2520.9 (4.47)	473.7 (7.26)
Tea (kg)	671	1018.6 (2.65)	883.1 (2.07)	135.5 (3.36)	671	1089.3 (2.49)	907.5 (1.97)	181.9 (3.18)	671	1078 (2.08)	942.7 (1.92)	135.3 (2.83)
Condiments (kg)	671	1014.4 (2.22)	880.9 (1.68)	133.5 (2.79)	671	1040.9 (2.07)	924.8 (1.78)	116.1 (2.73)	671	1046.8 (2.03)	914.1 (1.74)	132.7 (2.68)
Meat (kg)	671	1932.3 (2.09)	1560.9 (1.52)	371.5 (2.58)	671	1958.6 (2.03)	1713.7 (1.72)	244.9 (2.67)	671	1981.8 (1.87)	1730.6 (1.68)	251.2 (2.52)
Poultry (kg)	638	2100.7 (2.58)	1513.7 (1.37)	587 (2.92)	638	1987.8 (2.57)	1441.7 (1.34)	546.1 (2.90)	638	2123 (2.45)	1527.6 (1.32)	595.4 (2.78)

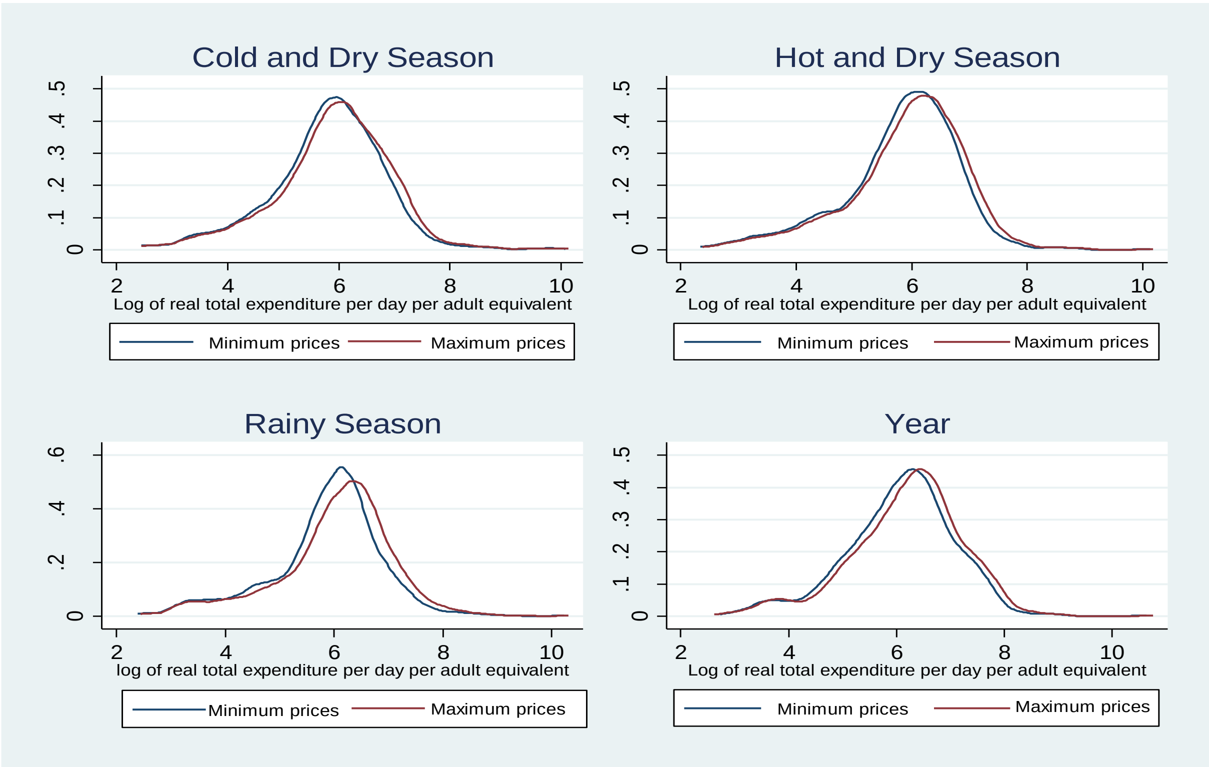
Notes: Pmin=Minimum price, Pmax=Maximum price. The values in parentheses are standard errors. The values presented in this table are means weighted by the sample weights.

The significant differences observed between the observed maximum and minimum food prices faced by the same household generate a corresponding gap in the valuation of food expenditure. As shown in Table 13 in the Online Appendix, the mean food expenditure per adult equivalent, evaluated at maximum prices, is 14, 14.3 and 24.6 percent greater in the cold and dry, hot and dry and rainy seasons, respectively, than that calculated using the minimum prices. Over the year, on average, the measured consumption increases by 17 percent when minimum prices are substituted with maximum prices.

Figure 1 presents the estimated densities of the log of real living standards variables annually and for each season, calculated with the observed minimum and maximum prices. Only food prices are recorded and can be used in the calculations of the real living standards and the food price indices, and the estimations in this paper. The specification of the living standard variable is made trickier by the fact that the studied agro-pastoral households can be both consumers and producers (and storers) of the goods included in the formulae of the price index. This would not be an issue if markets were perfects with no uncertainty, in which case one would expect that production and consumption decisions would be perfectly separated, and that the standard price index formulae would apply. However, these assumptions of perfect markets and absence of uncertainty are only approximate in rural Niger. The used price indices should therefore only be considered as approximating unfeasible price indices that would account for market imperfections and risk aversion. However, the used price indices are supported by the fact that finding price information about the products was not hard during the survey, which should not have been possible for extreme imperfections of markets and extreme impacts of uncertainties on the markets. Finally, the Laspeyres and Paasche price indices are the ones used in the huge majority of poverty studies that account for price differences around the world. Therefore, it makes sense to stick to this convention if we want to make statements about this widely spread methodology.

It seems fair to say that the shifts in these density curves caused by changing the type of price data are not dramatic. However, this is partly due to the logarithmic transformation that dampens income differences. The Laspeyres food price index is slightly sensitive to the choice of using the observed minimum or maximum prices. However, because the national average is used as the index base, the mean price index changes by less than one-half of a percent when substituting minimum prices with maximum prices in each season. We now turn to the estimation of the poverty measures.

Figure 1: Density of the Real Total Expenditure per Day and per Adult Equivalent (Epachenikov kernel estimator)



4. Results

We first examine the poverty estimates calculated for the whole year and based on comparing real living standard with the $1.90 a day international poverty line, then yearly and seasonal poverty estimates based on the estimated cost-of-basic-needs poverty lines. As usual, the poverty measures are calculated in terms of individuals, and the living standards in terms of adult equivalent[9].

4.1. Poverty estimates using the World Bank's international poverty line

The current World Bank's international poverty line is $1.90 per day per capita at 2011 PPP (Jolliffe and Beer Prydz, 2016). This poverty line is equivalent to $3.08 per adult equivalent per day in our case[10] and is applied to all regions of the country, which are regrouped into two larger regions: the North and the South. The North is formed by the regions of Agadez, Diffa, Maradi and Zinder, and the South is formed by the regions of Tahoua, Dosso and Tillabery.

Table 3: Poverty Measures Calculated with Minimum and Maximum Prices and the International Poverty Line

	National (N=671)			North (N=284)			South (N=387)			Difference between the North and the South (T-test)		
	FGT_0	FGT_1	FGT_2	FGT_0	FGT_1	FGT_2	FGT_0	FGT_1	FGT_2	FGT_0	FGT_1	FGT_2
Using maximum food prices	.735*** (.040)	.375*** (.047)	.246*** (.042)	.713*** (.044)	.347*** (.048)	.214*** (.042)	.749*** (.054)	.394*** (.071)	.268*** (.066)	-.036 (.080)	-.047 (.094)	-.054 (.085)
Using minimum food prices	.823*** (.037)	.425*** (.043)	.279*** (.042)	.819*** (.057)	.402*** (.049)	.249*** (.039)	.826*** (.055)	.441*** (.064)	.300*** (.065)	-.006 (.074)	-.039 (.085)	-.050 (.084)
Differences	-.088*** (.023)	-.050*** (.006)	-.032*** (.002)	-.106** (.039)	-.054** (.006)	-.035** (.003)	-.076*** (.029)	-.047*** (.009)	-.031*** (.003)	-.029 (.048)	-.007 (.012)	-.003 (.004)
Relative difference	-.11	-.12	-.11	-.13	-.13	-.14	-.09	-.11	-.10	4.83	.18	.06

Note: The values in parentheses are standard errors, and *,** and *** indicates significance at the 10, 5 and 1 percent level, respectively. The national poverty measures are computed with the regional poverty lines. The North represents the regions of Agadez, Diffa, Maradi and Zinder, and the South represents the regions of Tahoua, Dosso and Tillabery. FGT0 is the poverty head-count ratio, FGT1 is the poverty gap index and FGT2 is the poverty severity index.

As seen in Table 3, the poverty estimates obtained using the two types of food prices are significantly different. The estimated sampling errors account for the

[9] As pointed out in Milanovic (2002), in that case the poverty gap measure lives its interpretation in terms of total amount to give to the poor to lift them up to the poverty line. However, the poverty measure is still a correct poverty indication in this case and we still call it 'poverty gap' as often done.

[10] This number is obtained by multiplying the $ 1.90 per capita per day poverty line by the average household size (7.11) and dividing it the average adult-equivalent scale (4.39). The conversion rate of PPP used for 2016 is FCFA 220.6 for $ 1 PPP for private consumption. (source: https://data.worldbank.org/indicator/PA.NUS.PRVT.PP?locations=NE, consulted 14 March 2020).

complex sample design effects, while this does not seem to make much difference with these data.

Of course, since the poverty line level does not change when using either type of price information, the poverty measures obtained with the observed maximum prices are smaller than those obtained with the observed minimum prices. At the national level and for the North, the incidence of poverty measured with maximum prices (73.5 percent and 71.3 percent, respectively) is almost one-tenth smaller than that obtained with minimum prices (82.3 percent and 81.9 percent, respectively), which is substantial. This difference is less pronounced for the South, where the poverty incidence estimated with the minimum prices (82.6 percent) is only 7.6 percent greater than that obtained with maximum prices (74.9 percent). As a consequence, the ranking of regions according to poverty is reversed by substituting the type of price information used. Indeed, the differences in the estimated poverty rates caused by this change in price information are greater than the poverty difference between the North and South, which is only almost 1 percent when using minimum prices and 4 percent when using maximum prices. This matters if the national poverty alleviation strategy tends to target regions where poverty is found to be more severe, which is generally the case.

When considering poverty measures that are sensitive to living standard differences among poor individuals, the same substantial impact of choosing the price type emerges. Poverty intensity and poverty severity estimated with minimum food prices are 4 to 5 percent and 3 percent significantly greater, respectively, than those estimated with maximum food prices, depending on the region. However, this impact is smaller than the North-South poverty gaps, and therefore, the ranking of the regions does not reverse. Let us now turn to poverty estimates based on comparing real living standard with a poverty line stipulated from minimal nutritional requirements.

4.2 Poverty estimates with cost-of-basic-needs poverty lines

The sign of the effect when using minimum prices instead of maximum prices for estimating poverty is theoretically ambiguous. Prices intervene at four stages of the estimation process: (1) the construction of the consumption aggregate for each household, (2) the construction of each household price index, (3) valuing the minimal calorie requirement and finally, (4) the extrapolation of the poverty line when using an estimated Engel curve that also involves price effects.

We estimated three types of poverty indicators: annual poverty, which is defined as the arithmetic average of the three seasonal poverty indices; chronic poverty, which is formulated by considering the poverty measures applied to total annual consumption expenditure and therefore assumes that households smooth their consumption over the year; and finally, transient poverty, which is specified as residual poverty after accounting for chronic poverty in annual poverty (see the Online Appendix for more details on how these poverty measures are computed). Ravallion (1988) proposed using this dynamic decomposition, and Muller (2008) extended it to seasonal variations as a convenient way to assess the basic magnitude of the contribution of transient variations in well-being to poverty. Using data from Pakistan, Kurosaki (2006) emphasizes the sensitivity of this type of decomposition with respect to the poverty line, which supports examining poverty line estimates with the two type of price information.

Of course, more sophisticated approaches could be based on modeling consumption smoothing and the risk-sharing behavior of households, such as in Deaton and Paxson (1994). However, these methods could not be used with the data employed by the current study, and we prefer to employ methods that do not depend on specific hypotheses about behavior.

Absolute poverty lines

The absolute poverty lines are estimated using the cost-of-basic-needs method (see the Online Appendix for details). Table 10 in the online appendix shows that the estimated poverty lines are substantially higher when using maximum prices than minimum prices for all seasons and all regions. Over the year, the poverty lines calculated by using maximum prices are greater than those with the minimum food prices by almost 14 percent, and they slightly vary between regions. The gaps between these two kinds of estimated poverty lines are more pronounced in the rainy season (between 15 and 20 percent) and the hot and dry season (8 and 9 percent) than in the cold and dry season (7 and 12 percent).

The seasonal variations in the diverse poverty lines are greater than their regional variations. The seasonal absolute poverty lines lie between 220 and 333 CFA per day per adult equivalent, while over the year, their values lie between 240 and 279 CFA per day per adult equivalent, depending on the region. In addition, the gap between the poverty lines alternatively estimated with minimal and maximal prices also dominates the variation in the poverty lines between the two regions.

Seasonal poverty

The results of the seasonal poverty estimates are presented in Table 4[11]. For all three seasons, the two seasonal poverty estimates with alternative prices always differ at the 1 percent level of significance. However, the differences due to using alternative price information are always relatively moderate, with the greatest magnitude reaching slightly more than a 7 percent variation, but these differences can also be positive or negative, with no obvious structure determining these signs. It seems that, in that case, the poverty line estimation has partly compensated for the changes in living standards measures computed by using alternative price.

For the cold and dry season (see Table 4), the impact of using minimum prices versus maximum prices is more pronounced for the North and South than when considering the country as a whole. During this season, the poverty rate varies from 27.7 to 33.5 percent, while poverty intensity and poverty severity range from 10 to 16 percent and from 5 to 10 percent, respectively, depending on the region and the use of alternative prices. Moreover, the differences in the poverty rates in the North and the South are larger when they are assessed with minimum prices than maximum prices, while they are larger for poverty intensity and poverty severity when using maximum prices than minimum prices.

[11] In this and the following poverty tables, the standard errors are estimated using a bootstrap procedure, which is asymptotically equivalent to asymptotic formulae of standard errors for the sampling schemes, and should provide more accurate standard error estimates for small samples. However, computed poverty lines are considered as is always the case in the poverty literature. Accounting for the impact of sampling on poverty variations may make the result less significant, this concern is not typically considered in official poverty statistics.

Table 4: Poverty with the Absolute Poverty Line with Minimum and Maximum Prices

	National (N=671)			North (N=284)			South (N=387)			Difference between the North and the South		
	For the Cold and Dry Season											
	FGT_0	FGT_1	FGT_2	FGT_0	FGT_1	FGT_2	FGT_0	FGT_1	FGT_2	FGT_0	FGT_1	FGT_2
Using maximum food prices	.306*** (.069)	.144*** (.036)	.088*** (.024)	.291*** (.073)	.118*** (.037)	.061*** (.022)	.315*** (.107)	.162*** (.056)	.107*** (.038)	-.024 (.140)	-.043 (.073)	-.046 (.048)
Using minimum food prices	.310*** (.069)	.146*** (.037)	.090*** (.024)	.293*** (.073)	.116*** (.037)	.060*** (.022)	.321*** (.107)	.167*** (.058)	.111*** (.039)	-.028 (.140)	-.050 (.075)	-.051 (.050)
Differences	-.004** (.002)	-.002** (.001)	-.002** (.001)	-.002 (.002)	.002** (.001)	.001 (.001)	-.006** (.003)	-.005*** (.002)	-.004** (.002)	.004 (.004)	.007** (.003)	.005*** (.002)
Relative difference	-.013	-.014	-.022	-.007	.017	.017	-.019	-.030	-.036	-.142	-.140	-.098
	For the Hot and Dry Season											
Using maximum food prices	.312*** (.064)	.136*** (.032)	.083*** (.022)	.277*** (.078)	.103*** (.034)	.053*** (.020)	.335*** (.095)	.159*** (.050)	.104*** (.035)	-.057 (.130)	-.055 (.065)	-.050 (.045)
Using minimum food prices	.307*** (.061)	.136*** (.032)	.083*** (.022)	.292*** (.077)	.102*** (.033)	.052*** (.019)	.317*** (.089)	.160*** (.050)	.104*** (.035)	-.025 (.124)	-.058 (.064)	-.052 (.044)
Differences	.005 (.007)	.000 (.001)	.000 (.001)	-.014 (.010)	.001 (.002)	.001 (.001)	.018 (.010)	-.001 (.001)	.000 (.001)	-.032** (.015)	.003 (.002)	.002** (.001)
Relative difference	.016	.000	.000	-.051	.009	.019	.056	-.006	.000	1.28	-.051	-.038
	For the Rainy Season											
Using maximum food prices	.332*** (.064)	.157*** (.036)	.102*** (.025)	.317*** (.072)	.116*** (.035)	.066*** (.022)	.342*** (.098)	.185*** (.057)	.126*** (.040)	-.025 (.130)	-.069 (.073)	-.060 (.051)
Using minimum food prices	.337*** (.063)	.157*** (.036)	.101*** (.026)	.343*** (.065)	.120*** (.034)	.067*** (.022)	.333*** (.098)	.182*** (.057)	.124*** (.041)	.01 (.127)	-.062 (.073)	-.057 (.051)
Differences	-.005 (.009)	.000 (.002)	.001 (.001)	-.026 (.020)	-.004** (.002)	-.001 (.001)	.009** (.005)	.003* (.002)	.002 (.002)	-.035* (.018)	-.007** (.003)	-.003 (.003)
Relative difference	-.015	.000	.009	-.075	-.033	-.015	.027	.016	.016	-3.5	.11	.053

Note: The values in parentheses are standard errors, and *,** and *** indicates significance at the 10, 5 and 1 percent level, respectively. The national poverty measures are computed with the regional poverty lines.

In all regions the poverty rates estimated for the hot and dry season (see Table 4) are generally higher than those obtained for the cold and dry season. The poverty rate extends from 29 to 32 percent, while poverty severity and the poverty gap vary from 0.06 to 0.11 and from 0.116 to 0.167 percent, respectively, depending on the region and the prices used. The regional discrepancy in poverty is more pronounced than the gap between the two poverty estimates using alternative price information.

Finally, the poverty measures estimated for the rainy season are higher than those estimated for the two other seasons. The results may differ because the rainy season is a lean period for agropastoral households. Indeed, during this season, the head-count index of poor individuals moves from 31 to 34 percent, while poverty severity and the poverty gap vary from 0.066 to 0.126 and from 0.12 to 0.18, respectively, depending on the region and the type of prices used. In all seasons, there is more poverty in the South than in the North, except for the rainy season, which follows an opposite pattern.

Annual, chronic, and transient poverty

As previously mentioned, the annual poverty measures are defined as the arithmetic means of the seasonal poverty measures (see the Online Appendix for details). Table 5 shows that the annual poverty rates among agropastoral households remain stable for all regions and types of price used at 31.7 and 31.8 percent for the whole country, 29 and 31 percent for the North, and 32 to 33 percent for the South. Moreover, annual poverty severity, which lies between 0.146 and 0.147 for the whole country, is higher in the South than in the North. The estimated poverty measures are generally lower (or almost equal) when using maximum food prices than when using minimum food prices. The only exception is the head-count index of the North, which is approximately five percent higher when using minimum prices. However, the differences in annual poverty intensity and poverty severity using alternative price information are always very small and even insignificant in one-half of the cases.

Table 5: Annual Poverty with the Absolute Poverty Line (with Minimum and Maximum Prices)

	National (N=671)			North (N=284)			South (N=387)			Difference between the North and the South		
	Annual Poverty											
	FGT_0	FGT_1	FGT_2	FGT_0	FGT_1	FGT_2	FGT_0	FGT_1	FGT_2	FGT_0	FGT_1	FGT_2
Using maximum food prices	.317*** (.065)	.146*** (.034)	.091*** (.023)	.295*** (.073)	.113*** (.035)	.060*** (.021)	.331*** (.099)	.168*** (.054)	.112*** (.037)	-.036 (.132)	-.056 (.070)	-.052 (.047)
Using minimum food prices	.318*** (.063)	.147*** (.035)	.091*** (.024)	.309*** (.070)	.113*** (.034)	.060*** (.020)	.324*** (.097)	.169*** (.055)	.113*** (.038)	-.014 (.128)	-.057 (.070)	-.053 (.048)
Differences	-.001 (.004)	-.001 (.001)	.000 (.001)	-.014* (.007)	.000 (.001)	.000 (.001)	.007* (.004)	-.001 (.001)	-.001 (.001)	-.021*** (.008)	.001 (.002)	.001 (.002)
Relative difference	-.003	-.006	.000	-.045	.000	.000	.021	-.006	-.009	1.5	-.017	-.019
	Chronic Poverty											
Using maximum food prices	.265*** (.052)	.112*** (.027)	.063*** (.018)	.270*** (.070)	.095*** (.031)	.044*** (.017)	.262*** (.075)	.123*** (.041)	.076*** (.028)	.007 (.106)	-.028 (.055)	-.032 (.036)
Using minimum food prices	.273*** (.048)	.109*** (.026)	.061*** (.017)	.270*** (.069)	.098*** (.032)	.047*** (.018)	.275*** (.066)	.117*** (.039)	.070*** (.026)	-.005 (.097)	-.018 (.053)	-.023 (.034)
Differences	-.008 (.010)	.003 (.002)	.002** (.001)	.000 (.012)	-.003 (.002)	-.003*** (.001)	-.013 (.014)	.006*** (.002)	.006*** (.002)	.013 (.019)	-.009*** (.003)	-.009*** (.003)
Relative difference	-.029	.027	.033	.000	-.03	-.064	-.047	.051	.085	-2.6	.5	.39
	Transient Poverty											
Using maximum food prices	.051 (.032)	.034* (.018)	.028** (.012)	.025 (.064)	.017 (.040)	.015 (.025)	.068** (.031)	.045*** (.016)	.036*** (.012)	-.043 (.066)	-.028 (.039)	-.020 (.026)
Using minimum food prices	.044 (.035)	.037** (.020)	.030** (.014)	.038 (.068)	.014 (.040)	.012 (.025)	.048 (.037)	.052*** (.020)	.042*** (.015)	-.009 (.073)	-.038 (.042)	-.030 (.028)
Differences	.007 (.011)	-.003 (.002)	-.003 (.002)	-.013 (.014)	.003 (.002)	.003 (.002)	.020 (.013)	-.007** (.003)	-.006** (.003)	-.034* (.020)	.010*** (.004)	.010*** (.003)
Relative difference	.16	-.081	-.10	-.34	.21	.25	.42	-.13	-.14	3.78	-.26	-.33

Note: The values in parentheses are standard errors, and *,** and *** indicates significance at the 10, 5 and 1 percent level, respectively. The national poverty measures are computed with the regional poverty lines.

Table 5 displays the estimates of chronic poverty, which is the closest estimation to typically published poverty statistics, which are based on annual consumption indicators. The results show moderate poverty levels among agropastoral households, approximately 27 percent for the head-count index, as expected, with households deemed to be generally better off than most other Nigerien households. The results again show that poverty is more severe in the South than in the North, even though there may appear to be a smaller proportion of poor individuals in the South when using maximum prices. This result is consistent with national statistics on poverty published in 2011 and indicates that 52.2 percent of poor individuals live in the South, while 47.8 percent live in the North (Institut National de la Statistique, 2013). Moreover, according to the Institut National de la Statistique (2017), in 2011, in Niger, 29.9 percent of poor individuals and 19.7 percent of nonpoor individuals lived in agropastoral areas.

Calculating chronic poverty using the mean living standards across seasons changes the national head-count index results little (27.3 percent with maximum prices and 26.8 percent with minimum prices). Even though these changes are larger for the poverty gap (0.124 with maximum prices vs 0.123 with minimum prices) and poverty severity (0.075 with maximum prices vs 0.074 with minimum prices), the impact of choosing one type of price remains negligible.

On the whole, distinguishing the minimum prices and maximum prices only slightly, although significantly, affects the estimate of chronic poverty at the national level, which is only slightly higher with minimum prices. Similar marginal effects can be found for each region, with, again, opposite patterns. The poverty gap and poverty severity are slightly higher in the North when using minimum prices and in the South when using maximum prices.

Table 6: Percentage of Transient Poverty in Annual Poverty

	National (N=671)			North (N=284)			South (N=387)			Difference between the North and the South		
	FGT_0	FGT_1	FGT_2	FGT_0	FGT_1	FGT_2	FGT_0	FGT_1	FGT_2	FGT_0	FGT_1	FGT_2
Using maximum food prices	15.77	23.29	30.77	8.47	15.04	25	20.54	26.78	32.14	-12.07	-11.74	-7.14
Using minimum food prices	13.84	25.17	32.97	12.30	12.40	20	14.81	30.77	37.17	-2.51	-18.37	-17.17
Differences	1.93	-1.88	-2.2	-3.83	2.64	5	5.73	-3.99	-5.03	-9.56	6.63	10.03
Relative difference	.12	-.08	-.07	-.45	.17	.2	.28	-.15	-.16	.79	-.56	-1.40

Finally, Tables 5 and 6 show that using one kind of price is found to have greater consequences for estimated transient poverty. The seasonal transient poverty rates are significantly higher at the national level (5.1 percent vs 4.4 percent) and in the South (6.8 percent vs 4.8 percent) when using maximum prices and lower in the North (2.5 percent vs 3.8 percent). The opposite pattern is observed for transient poverty severity and the poverty gap across regions. Note that, again, the ranking of the two regions in terms of poverty rates is reversed, which hints at numerous crossings of the poverty line by households in some seasons in a context of high levels of chronic poverty. However, the share of transient poverty in annual poverty remains relatively modest, nationally and for each season. When using maximum prices, the poverty rate (poverty severity) ranges from 8 percent in the North to 20 percent in the South (0.25 and 0.32). This result suggests that pastoral activities are particularly effective for smoothing seasonal consumption shocks and thereby limiting the role of transient poverty. In addition, these moderate fluctuations of poverty over seasons are relatively robust to the choice of the type of prices used, especially from a national perspective.

5 Conclusion

Price deflation is a fundamental step in the construction of living standard indicators for poverty analyses. However, rather than facing a unique price for each given product, as typically assumed, each household faces an different realizations of prices in a given period. We show that this specific price information can be used to generate an interval of poverty estimates, which partially identifies the poverty levels, and this information may affect poverty alleviation policies.

To conduct this analysis, we use a unique dataset from Niger compiled from a survey in which agropastoral households provide information about the minimum and maximum prices they paid in each season for each consumed food product.

Then, we estimate poverty measures based on these alternative price data and three alternative poverty lines: The World Bank international poverty line of 1.90 PPP US $, an estimated absolute poverty line based on minimum prices, and a similar poverty line based on maximum prices.

The results show statistically significant differences in the estimated poverty levels obtained with these three approaches, whether they are used for international annual poverty comparisons or seasonal transient poverty analyses. As a consequence, the typically estimated poverty statistics, which consider that each household, cluster, or region, face a unique price for each product at a given period, may be less accurate than often believed, at least for these latter two analyses. In particular, the impact of alternatively using observed minimum and maximum prices for computing real living standards is found to generate gaps in the estimated poverty rates for Nigerien agropastoral households that are larger than the corresponding gaps between the estimated poverty in the South and North regions. A policy consequence of these differences is that the targeting priorities of the regions in terms of food aid or cash transfer programs included in poverty alleviation policies would be reversed between the South and the North by using maximum prices instead of minimum prices when monitoring poverty.

The consequences for poverty alleviation policies are therefore substantial. First, notwithstanding the source of price dispersion (e.g, quality differences, measurement errors, or pure randomness), caution is advised when using typical poverty statistics that do not account for the dispersion of the realized prices that each household faces, which is the only current standard practice. The estimated gaps between the results based on using the observed minimal and observed maximal prices, in the case of agropastoral households in Niger, are large enough to indicate that prudence is needed. Besides, in the studied context, substantial quality differences for cereal products are implausible. Second, policies changing price distributions may affect measured poverty in complex ways, for example, when the impacts differ for the observed minimum, maximum, and mean prices faced by each household. The latter may be the case for public price subsidies that may put more pressure on the maximum prices paid by consumers than on the minimum prices if they are below the legal subsidy price level.

A few issues remain that have to be resolved in a broader context. First, richer data covering whole countries and detailed consumption and price information over several years and their seasons allow a more precise exploration of the issues uncovered here. Second, the respective determinants of maximum and minimum prices need to better theoretically and empirically understood.

Some new avenues of research could be developed from this initial exploration. First, poverty estimators based on partial identification could be thoroughly developed and implemented, for example by accounting not only for individual price dispersion, but also for measurement errors in consumption. Second, the economic determinants of the observed gaps in minimum and maximum prices paid by the same household in the same period need to be better understood, in particular since there are hints in these data that these gaps are not overly caused by quality choices. Third, the distributions of price realizations faced by typical households should be more systematically investigated. Fourth, minimum and maximum prices could be used for analyses other than those estimating poverty. For example, these prices can be alternatively included in demand system estimation. Fifth, it is unclear whether minimum and maximum prices have the same economic and normative importance. For example, maximum prices may sometimes correspond to emergency circumstances or even forced purchases, which points to high priority given to social relief.

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