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Université Clermont Auvergne, CNRS, IRD, CERDI, F-63000 Clermont-Ferrand, France

POVERTY-ALLEVIATING POLICIES FOR AGRICULTURAL HOUSEHOLDS IN THE SAHEL

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Nouréini SAYOUTI SOULEYMANE

Sous la direction de Mme. Catherine ARAUJO
et de Mr. Christophe MULLER

Membres du jury

Vianney DEQUIEDT	Professeur, Université Clermont Auvergne	Président
Karen MACOURS	Directrice de Recherche, INRAE et Professeur, PSE	Rapporteuse
Valérie BERANGER	Professeur, Université de Toulon	Rapporteuse
Christophe MULLER	Professeur, Ecole d'Economie d'Aix-Marseille	Co-directeur
Catherine ARAUJO	Chargée de Recherche, CNRS	Co-directrice

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Résumé

Cette thèse est formée de trois essais empiriques sur les politiques de réduction de la pauvreté pour les ménages agricoles dans le Sahel.

Le chapitre 1 étudie l'effet des distributions de prix idiosyncratiques auxquelles sont confrontés les ménages sur les estimations de la pauvreté en utilisant un ensemble de données unique au Niger dans lequel les ménages agro-pastoraux fournissent les prix minimum et maximum observés pour chaque saison. L'estimation de mesures de pauvreté basées alternativement sur ces données de prix distinctes, avec plusieurs méthodologies de calcul de seuils de pauvreté absolue, permet d'obtenir la plage potentielle de variation de la pauvreté générée par les distributions de prix idiosyncratiques. Les résultats montrent que l'utilisation des prix minimum et maximum génère des écarts dans l'estimation de la pauvreté pour ces ménages qui dépassent les disparités régionales de pauvreté. Cela implique que les priorités de ciblage régional dans les politiques de réduction de la pauvreté seraient inversées si ces prix alternatifs sont utilisés.

Le chapitre 2 propose une approche pour prédire la résilience des ménages. Cette approche combine un modèle de mélange gaussien et un réseau neuronal pour prédire la fonction de densité de probabilité du bien-être conditionnel spécifique à chaque ménage. Son score de résilience prédit peut être calculé comme une probabilité de rester au-dessus d'un seuil pré-spécifié. Nous évaluons l'approche proposée sur des données de ménages du Nigeria et la comparons à une approche de moment conditionnel communément utilisée dans la littérature sur la résilience. Les résultats mettent en lumière le potentiel de notre approche pour prédire avec plus de précision la résilience des ménages. Les résultats montrent également que, ne pas prédire correctement la fonction de densité de probabilité peut conduire à une surestimation du score de résilience prédit, ce qui a des implications sur la quantification de la prévalence de la résilience dans une population et de la quantité d'efforts nécessaires pour renforcer la résilience.

Le chapitre 3 étudie les mécanismes qui sous-tendent l'effet des politiques agricoles sur l'apport alimentaire des ménages pastoraux en utilisant une analyse de médiation statistique. Sur la base des données d'une enquête agropastorale menée au Niger, on constate que les effets des services de vulgarisation associés à un meilleur accès aux marchés opèrent principalement par le biais du profit pastoral du ménage. Cela n'est pas le cas des services vétérinaires privés et des programmes d'alimentation du bétail à faible coût. En outre, les services de vulgarisation pour l'élevage peuvent favoriser la spécialisation des ménages agropastoraux dans l'élevage de bovins et d'ovins, les incitant à s'orienter vers la transhumance pastorale et limitant leur accès aux céréales. Ces services peuvent donc nuire à leur apport calorique total.

Summary

This dissertation provides three empirical essays on poverty-alleviating policies for agricultural households in the Sahel.

Chapter 1 investigates the effect of idiosyncratic price distributions faced by households on poverty estimates by using a unique dataset from Niger in which agro-pastoral households provide the observed minimum and maximum prices in each season. Estimating poverty measures alternatively based on these distinct price data, with several absolute poverty line methodologies, elicit the potential range of poverty assessments generated by idiosyncratic price distributions. The results show that using minimum and maximum prices generates gaps in the estimated poverty for these 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.

Chapter 2 proposes an approach to predicting household resilience. The proposed approach combines a Gaussian Mixture Model and a Neural Network to predict household-specific conditional well-being probability density function. Its predicted resilience score can be computed as a probability of remaining above a prespecified threshold. We evaluate the proposed approach to household data from Nigeria and compare it to a conditional moment approach commonly used in the development resilience literature. The results shed light on the potential of our approach to accurately predict household resilience. Also, the results show that not accurately predicting the probability density function may lead to overestimating the predicted resilience score, which has implications for quantifying the prevalence of resilience in a population and the amount of effort needed to build resilience.

Chapter 3 investigates the mechanisms underlying the effect of agricultural policies on pastoralist households' dietary intake by using statistical mediation analysis. Based on data from an agro-pastoral survey conducted in Niger, the effects of livestock extension services associated with better access to markets are found to operate mainly through a household's pastoral profit. At the same time, this is not the case for private veterinary services and low-cost livestock feed programs. In addition, livestock extension services may foster agro-pastoral households' specialization in cattle and sheep rearing, incentivizing them to switch toward pastoral transhumance and limiting their access to cereals. As a result, livestock extension services are found to damage their total calorie intake.

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Introduction

La région du Sahel est l'une des plus pauvres du monde. L'Organisation des Nations unies pour l'alimentation et l'agriculture estime qu'en moyenne 20 millions de personnes souffrent de malnutrition et d'insécurité alimentaire dans la région chaque année, principalement pendant la période de soudure (Spano, 2016). Elle estime également qu'en 2016, près de 6 millions d'enfants de moins de cinq ans souffrent de malnutrition aiguë, et que la sous-nutrition est la principale cause d'un tiers de la mortalité infantile.

Depuis des décennies, les pays de cette région ont tenté, individuellement ou collectivement, d'apporter des solutions diverses et variées en termes de politiques agricoles à ce problème. L'un des secteurs clés sur lequel ces politiques se sont concentrées est le pastoralisme qui est une activité bien adaptée aux conditions agro-écologiques de cette région et qui constitue également la principale source de revenus pour de nombreux ménages.

Dans un soucis d'aider les ménages à faire face à plusieurs risques et chocs présents ou futurs, les gouvernement de ces pays prônent également la mise en place de filets sociaux au profit des ménages les plus pauvres et vulnérables (Beegle et al., 2018). Des programmes soutenus par les bailleurs de fonds. Mais dans un contexte de forte contrainte budgétaires, il est important de pouvoir identifié avec le moins d'erreur possible les ménages pauvres ou vulnérables (Del Ninno and Mills, 2015). Les statistiques de mesure de la pauvreté aujourd'hui sont beaucoup utilisées pour cibler les ménages pauvres et identifier les zones avec le plus de pauvreté, qui seront prioritaires pour l'allocation des fonds (Del Ninno and Mills, 2015).

La déflation des prix est un élément majeur de l'analyse des niveaux de vie et de la pauvreté dans les économies en développement comme ceux du Sahel. C'est notamment le cas dans les pays pour lesquels les différences de prix spatiales et temporelles auxquelles les ménages sont confrontés peuvent être substantielles. La grande dispersion des prix sur les marchés est une caractéristique générale des économies en développement, notamment en raison des coûts de transport et des achats en gros (Attanasio and Frayne, 2006; Broda et al., 2009; Atkin and Donaldson, 2015). Dans certains contextes, principalement pour les zones urbaines, seules de faibles différences spatiales de prix ont été constatées (Musgrove and Galindo, 1988; Gibson and Kim, 2015; DellaVigna and Gentzkow, 2019).

La déflation s'est avérée cruciale dans l'estimation des seuils et des indicateurs de pauvreté. Par exemple, des biais importants dans les estimations de la pauvreté chronique et transitoire découlent des écarts de prix saisonniers et géographiques entre les ménages au Rwanda (Muller, 2008).

La prise en compte des écarts de prix peut également améliorer les politiques de réduction de la pauvreté, par exemple, dans le cadre de programmes de transferts ciblés contre la pauvreté, tels que ceux introduits pour la première fois par Muller and Bibi (2010), avec des niveaux de vie déflatés par des indices de prix réels estimés en Tunisie. Dans ce cas, des informations plus précises sur les prix ont amélioré l'efficacité du ciblage des politiques sociales et réduit le besoin de fonds sociaux.

Toutefois, l'un des problèmes qui se posent lorsqu'on envisage la correction des prix dans l'analyse de la pauvreté est qu'un ménage peut être confronté à une distribution de prix différents pour le même produit au cours de la même période. Un problème qui est abordé dans le chapitre 1 de cette thèse, où les effets de cette distribution de prix au niveau des ménages, sur les indicateurs de pauvreté, et sur les politiques de ciblages des zones les plus pauvres, sont analysés.

Outre la pauvreté, la notion la plus débattue parmi les praticiens du développement, la résilience et la vulnérabilité, commencent par susciter l'intérêt. En effet, l'intérêt principal de ces deux notions réside dans le fait que les agences de développement et humanitaires veulent pouvoir mettre en place des actions pour éviter que les ménages ne tombent dans la pauvreté.

Les fondements théoriques et les méthodologies empiriques de la mesure de la résilience ont été validés par les chercheurs dans plusieurs articles scientifiques[1] appartenant à un courant de recherche appelé "résilience du développement." Cependant, Upton et al. (2022) montrent que les méthodes courantes utilisées pour mesurer la résilience souffre d'un taux élevé de faux positifs et de faux négatifs. Le chapitre 2 de cette thèse contribue à cette littérature de la résilience en proposant une approche de mesure de la résilience combinant un modèle de mélange gaussien et un réseau neuronal.

Les politiques agricoles des pays en développement sont souvent motivées par l'amélioration de l'état nutritionnel des populations rurales. Ces politiques sont généralement conçues dans l'optique d'augmenter les revenus de production des ménages agricoles ou pastoraux. Dans la littérature, trois voies potentielles reliant l'agriculture et la nutrition ont été étudiées au niveau des ménages : la production alimentaire pour l'autoconsommation, les revenus agricoles pour les dépenses en produits alimentaires et non alimentaires et enfin l'autonomisation des femmes impliquées dans les activités agricoles (The World Bank, 2007; Herforth and Harris, 2014). La première est plus directe et particulièrement pertinente pour les ménages agricoles de subsistance ou de semi-subsistance. En effet, l'augmentation du niveau de la production alimentaire d'un ménage devrait généralement accroître sa disponibilité alimentaire et, par conséquent, son apport alimentaire. Cependant, les ménages agricoles étant de plus en plus orientés vers le marché, ils achètent une part impor-

[1] Cissé and Barrett (2018); d'Errico and Di Giuseppe (2018); d'Errico et al. (2020) parmi tant d'autres.

tante de leur nourriture sur le marché pour satisfaire leurs besoins alimentaires. En outre, grâce à l'accès aux marchés et aux revenus supplémentaires tirés de la vente des produits, ils peuvent acheter des aliments de meilleure qualité. Cela correspond à la deuxième voie d'action. La troisième voie est plus directement liée aux résultats de la nutrition des enfants, puisqu'il a été constaté que les femmes s'occupent mieux des enfants que les hommes, et que les politiques traitant des questions de nutrition sont souvent plus efficaces lorsqu'elles ciblent les femmes.

Les études mentionnées ci-dessus soulignent la nature complexe de la relation entre l'agriculture et la sécurité alimentaire et nutritionnelle des ménages et mettent l'accent sur d'autres facteurs (par exemple, l'allocation des ressources, la dynamique intra-ménage et les réseaux) qui peuvent affecter cette relation. Toutefois, les mécanismes par lesquels les politiques agricoles affectent l'apport alimentaire des ménages restent largement méconnus. Le chapitre 3 de cette thèse contribue à cette littérature en cherchant à savoir si les politiques agricoles ont un impact positif sur les revenus agricoles des ménages et si cet impact positif se traduit pleinement dans les apports alimentaires des ménages. Ce qui contribuera à faire la lumière sur ces mécanismes liant l'agriculture et les apports alimentaires et diététiques des ménages ruraux.

En s'inspirant de la tendance actuelle des thèses en économie, ce manuscrit compile trois essais empiriques qui contribuent à la littérature sur l'analyse des politiques de réduction de la pauvreté pour les ménages agricoles. Indépendants les uns des autres, les chapitres possèdent leur propre introduction, méthodologie, base de données et résultats. Le choix des pays d'étude (le Niger et le Nigéria) découle naturellement de la disponibilité des données et de leur pertinence dans l'illustration des questions de recherche. Bien qu'indépendant, ces travaux sont le fruit d'une réflexion globale sur les politiques de réduction de la pauvreté pour les ménages agricoles dans le Sahel. En particulier, ces chapitres prêtent attention à certains aspects de mesure de pauvreté, de résilience et d'analyse des effets des politiques agricoles négligés dans la littérature économique et espèrent apporter des outils d'aide à la conception de politiques plus efficaces dans la lutte contre la pauvreté.

La suite de cette introduction propose un résumé de chacun des chapitres. Enfin, les implications des résultats suggérés par cette thèse, ainsi que les recommandations de politiques économiques associées, sont détaillées en conclusion.

Chapitre 1 "How does information on minimum and maximum food prices affect measured monetary poverty? Evidence from Niger".

Actuellement, les écarts de prix dans les estimations des seuils de pauvreté sont principalement pris en compte en estimant différents seuils de pauvreté pour différentes strates géographiques. En outre, les indices de prix régionaux sont généralement utilisés pour déflater les niveaux de vie dans les analyses de la pauvreté. Cela peut poser problème si les ménages sont effectivement confrontés à des distributions de prix idiosyncratiques qui ne peuvent être bien résumées par des indices de prix agrégés (c'est-à-dire des prix différents pour le même produit à la même période pour le même ménage).

Cette question est étudiée à l'aide d'un ensemble unique de données du Niger dans lequel les ménages agropastoraux fournissent les prix minimum et maximum observés pour chaque saison. L'estimation de mesures de pauvreté basées alternativement sur ces données de prix distinctes, avec plusieurs méthodologies de calcul de seuils de pauvreté absolue, permet d'obtenir la plage potentielle de variation de la pauvreté générées par des distributions de prix idiosyncratiques.

Des différences statistiquement significatives apparaissent dans l'estimation des pauvretés chroniques et dynamiques pour ces approches, en particulier pour les comparaisons internationales de la pauvreté et le suivi de la pauvreté transitoire saisonnière. Plus précisément, l'utilisation des prix minimum et maximum génère des écarts dans l'estimation de la pauvreté des ménages agropastoraux nigériens qui dépassent les disparités régionales de pauvreté. Cela implique que les priorités de ciblage régional dans les politiques de réduction de la pauvreté (par exemple, la localisation des projets de développement, les allocations régionales des fonds de transfert d'argent) seraient inversées si ces prix alternatifs sont utilisés.

Chapitre 2 "Predicting Resilience against Poverty with Machine Learning: Evidence from Nigeria".

Ce chapitre propose une approche pour prédire la résilience des ménages. L'approche proposée définit la résilience comme une probabilité de rester au-dessus d'un certain niveau de vie minimal en fonction de certaines caractéristiques observables et de l'exposition aux chocs. Elle s'appuie également sur la mesure de la résilience basée sur une approche de moment conditionnel communément utilisée dans la littérature sur la résilience, qui sert de référence.

Notre approche combine un modèle de mélange gaussien et un réseau neuronal pour prédire la fonction de densité de probabilité du bien-être conditionnel spécifique au ménage, à partir de laquelle le score de résilience prédit peut être calculé comme une probabilité de rester au-dessus d'un seuil pré-spécifié.

Nous évaluons l'approche proposée sur des données de ménages du Nigeria et la comparons à la séquence de deux régressions de l'approche de référence. Les résultats mettent en lumière le potentiel de notre approche à prédire avec plus de précision la résilience des ménages grâce à une prédiction correcte de sa fonction de densité de probabilité conditionnelle. De plus, les résultats montrent qu'une prédiction moins précise de la fonction de densité de probabilité peut conduire à une surestimation du score de résilience prédit, ce qui a des implications pour quantifier la prévalence de la résilience dans une population et la quantité d'effort nécessaire pour construire la résilience.

Chapitre 3 "How Do Agro-Pastoral Policies Affect the Dietary Intake of Agro-Pastoralists? Evidence from Niger".

Les politiques agricoles dans les pays ruraux pauvres en développement peuvent souvent améliorer la nutrition des ménages en augmentant le profit agricole des ménages et, par conséquent, leur apport alimentaire.

En utilisant une analyse de médiation statistique, nous étudions les mécanismes sous-jacents à l'effet des politiques agricoles orientées vers les ménages pastoraux sur leur apport alimentaire. Sur la base des données d'une enquête agropastorale menée en 2016 au Niger, on constate que les effets des services d'extension du bétail associés à un meilleur accès aux marchés opèrent principalement par le biais du profit pastoral d'un ménage, alors que ce n'est pas le cas pour les services vétérinaires privés et les programmes d'alimentation du bétail à faible coût. Les services de vulgarisation du bétail peuvent favoriser la spécialisation des ménages agropastoraux dans l'élevage de bovins et d'ovins, ce qui les incite à s'orienter vers la transhumance pastorale et limite leur accès aux céréales. Par conséquent, les services de vulgarisation de l'élevage nuisent à leur apport calorique total.

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Chapter 1

How does Information on Minimum and Maximum Food Prices affect Measured Monetary Poverty? Evidence from Niger

This chapter is joint work with Christophe Muller (AMSE).

1.1 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[1] 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, a distribution realizations of prices for the same product in the same period instead of a unique price. Does this change the perspective of poverty analyses? How are the price gaps currently accounted in poverty lines and poverty indicators ? Mostly, they are accounted by : (1) estimating different poverty lines for different geographical strata (usually regions), and (2) deflating living standards for mean price gaps across these strata. How is the household-specific price distribution addressed?

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). All these variants are extended to chronic and transient poverty measures across seasons.

As mentioned before, the effects of price gaps in poverty line and poverty estimates are mostly accounted by estimating different poverty lines for different geographical strata, mostly regions, and deflating living standards for mean price differences across these strata. This may be an issue if households actually face idiosyncratic price distributions inaccurately summarized by aggregated price indices. Our approach is to investigate it by comparing poverty estimates in Niger, using alternatively the minimum and maximum prices faced by each household in each season.

Indeed, let be a household in a given season facing a price index distribution for a price index variable p. Fixing its nominal living standard x implies that its expected real living standard is $y = E(x/p) = x/H$, where H is the unobserved harmonic mean of the distribution of p. Let be pmin (respectively, pmax) the minimum (respectively maximum) price index that it faces. Then, $x/pmax \leq y \leq x/pmin$. Therefore, using maximum (minimum) prices underestimates (overestimates) the real living standard, and therefore would overestimate (underestimate) poverty, keeping all other things constant.

On the other hand, in the absolute poverty line method, the 'food poverty line' zF is such that: $C^*pmincal \leq zF = C^*pcal \leq C^*pmaxcal$, where C is the calorie requirement per adult equivalent, pcal is the mean calorie price, pmincal (pmaxcal) is the

[1] Such as Sen (1982); Pinstrup-Andersen (1985); Stern (1989)

mean calorie price computed from minimum (maximum) prices, all these in each considered strata. Therefore, maximum (minimum) prices overestimate (underestimate) the food poverty line. Finally, the link between the poverty line z and the food poverty line is generally monotonic. This is strictly the case when the subjacent model is the almost ideal demand system. This is also expected most of the time when using the quadratic almost ideal demand system instead, since the quadratic term typically remains a minor empirical correction of the almost ideal demand system. As a consequence, due to the change in the poverty line, again using maximum (minimum) prices would overestimate (underestimate) poverty, keeping all other things constant.

Therefore, using alternatively minimum and maximum prices yields a partial identification of poverty by a lower (upper) bound based on minimum (maximum) prices. Moreover, it is not impossible that almost all actual prices be close to the minimum (or the maximum) prices, which implies that these poverty bounds are sharp.

Therefore, the role of the price distribution faced by each household can be investigated by examining these bounds. If there were no significant differences between these two poverty estimates, then we would be reassured that there is no need to account for these idiosyncratic individual price distributions. Otherwise, there may be a potentially important issue in poverty assessment, and poverty alleviation policies.

How does these estimates differ? The gaps that we find in poverty that are caused by using the observed minimum prices instead of maximum prices are considerable when considering the international poverty line. These gaps are also substantial for 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.

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. Large price dispersion across markets is a genera feature of developing economics, notably due to transport costs and bulk purchases (Attanasio and Frayne, 2006; Broda et al., 2009; Atkin and Donaldson, 2015). In some contexts, mainly for urban areas, only small spatial differences in price were found (Musgrove and Galindo, 1988; Gibson and Kim, 2015; DellaVigna and Gentzkow, 2019)

However, small price gaps and uniform pricing is likely more relevant for manufactured consumer products, which are almost negligible in the rural and peri-urban sample in this study. In Niger, Aker (2010) finds in 37 domestic markets that the substantial grain price dispersion observed across market dropped by 10 to 16 percent after the introduction of mobile phones.

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)[2]. These methods typically use cluster means to identify price variability, which may be a strong assumption if there are local, and even individual, dispersions in prices.

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. (2017)). For example, sizable biases in estimates of chronic and transient poverty arise from seasonal and geographical price gaps across households in Rwanda (Muller, 2008).

Accounting for price gaps can also improve poverty alleviation policies, for example, in focused antipoverty transfer schemes, such as those first introduced by Muller and Bibi (2010), with living standards deflated by estimated true price indices in Tunisia. In that case, more precise price information enhanced the targeting efficiency of social policies and reduced the need for social funds.

However, one issue when considering price correction in poverty analysis is that a household may face a distribution of 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. They 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 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).

Does this residual price dispersion, possibly occurring for each individual separately, regardless of its source : quality choice, social relations, transactions constraints or mere randomness, affects poverty measurement and policy? The aim of

[2]See also Deaton (1990, 1997); Crawford et al. (2003); Ayadi et al. (2003); Deaton and Dupriez (2011)

[3]See Ravallion and Bidani (1994); Rao (2000)

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

this study is to investigate this question in agropastoral households in Niger. Using alternative information, observed maximum and minimum household 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.

Which households would be missed by policies omitting household-specific price distribution, or using minimum or maximum prices as a basis? The studied changes in poverty estimates remain large enough to reverse the North vs South targeting priority in poverty alleviation policies (e.g. development project localization) that are derived from estimated poverty profiles. This is important in Niger because of a traditional political opposition between these areas. However, international donors tend to allocate their development funds to the regions that they assess as needier. In this context, establishing which region should be served first is crucial.

The rest of the paper is organized as follows. In Section 1.2, we present the context of Niger and the data used. Section 1.3 discusses the methods used to compute the poverty indices. Section 1.4 reports the estimation results. Finally, Section 1.5 presents the conclusion.

1.2 Context and Data

1.2.1 Survey data

Niger's economy is 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)). The data used in this study were obtained from a specialized survey collected by the Ministry of Livestock in Niger. This survey was conducted for 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 exclude urban and peri-urban households that are not part of our population of interest: the 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 lived 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 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 A5 of the 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[5] 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, which is driven by a food Engel curve estimation, may generate an additional

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

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, which is more time accurate than usual.

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).

1.2.2 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 SectionA1 of the Appendix for details).

Moreover, for some households and some products, the stated minimum and maximum prices are identical. Table 1.1 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 estimated 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[6]. 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[7] 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.

[6] 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).

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

Table 1.1: 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 A2 in the Section A2 of the Appendix . 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.

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 A4 in Section A3.5 of the 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.

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.

Figure A1 presents the estimated densities of the log of real living standards annually and for each season, calculated with the observed minimum and maximum prices. 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.

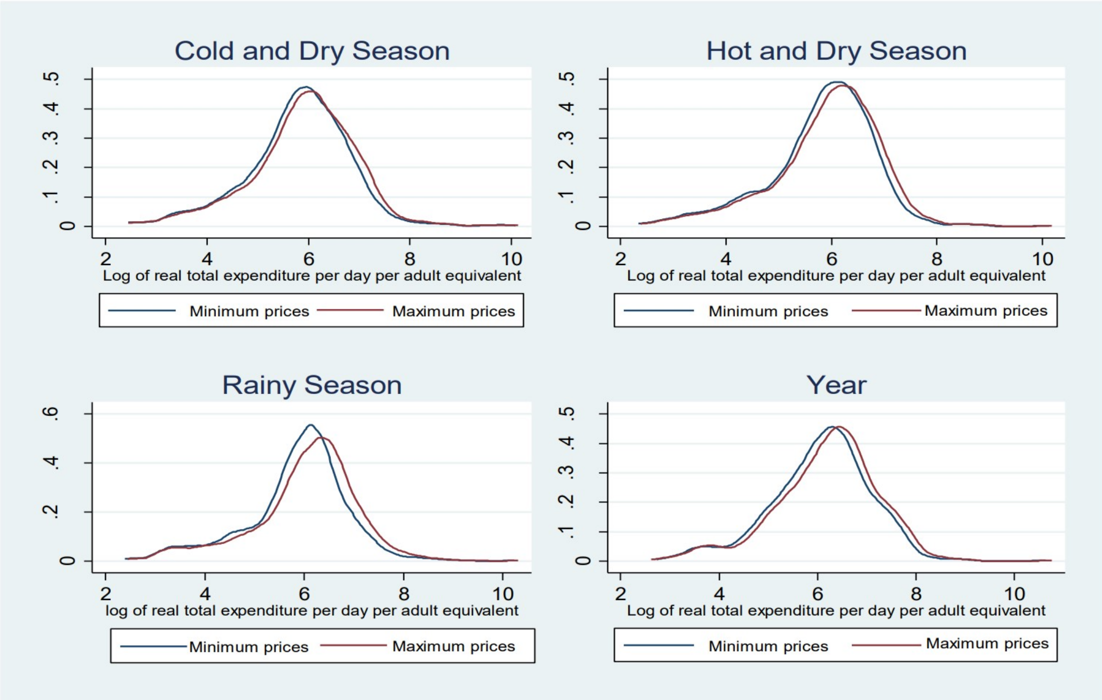

Figure 1.1: Density of the Real Total Expenditure per Day and per Adult Equivalent (Epachenikov kernel estimator)

1.3 Poverty measures

The poverty measures employed in this work are widely used in the literature on poverty and are typically based on household income or total consumption expenditure. Monetary poverty is defined as a shortfall in income or total expenditure, given a specified poverty line. In the literature, the most widely used monetary poverty indicators are from the Foster-Greer-Thorbecke (FGT) family (Foster et al., 1984).

$$FGT_\alpha = \frac{1}{\sum_{i=1}^{N} w_i \times T_i} \left[\sum_{i=1}^{N} w_i \times T_i \times \left(\frac{z-y_i}{z}\right)^\alpha \times I(y_i < z)\right]$$

where N is the number of households in our sample, y_i is the living standard of each household i, w_i is the household sample weight, T_i is family size, α is a parameter that can be viewed as describing poverty aversion, and z is the poverty line. The three values of α= 0, 1 and 2 correspond to the head-count ratio, the poverty gap index, and the squared poverty gap (poverty severity index), respectively. These indices are calculated at the aggregate level for the whole population and each of three seasons of the same agricultural year under study. These three seasons have the same length (four months) and are denoted as the *cold and dry season*, the *hot and dry season*, and the *rainy season*.

We use $y_{it} = c_{it}/(E \times FPI_{it})$ to denote the real living standards for household i in season t, where c_{it} is its total consumption expenditure in season t, E the adult equivalent scale and FPI_{it} its Laspeyres' food price index in season t calculated with the annual budget shares, the mean household over the year and the whole population as its base. Seasonal poverty is estimated by replacing y_i with y_{it} and using the corresponding seasonal poverty line z_t in the abovementioned FGT_α formula. Consumer price indices (CPIs) covering the whole consumption would be better, but in our case, there is no price information on nonfood products.

The annual living standard of household i over the studied agricultural year is equal to $y_i = c_i/(E \times FPI_i)$, where $c_i$represents household total annual consumption (the sum of the three seasonal consumption) and FPI_i is its Laspeyres' food price index over the year. When computing these living standards, we neglect the discount factor between the three seasons because of the short observation period.

In addition to seasonal poverty, three other poverty measures, namely, annual poverty, chronic poverty and transient poverty, are estimated. Following Muller (2008), annual poverty (AP) is defined as the arithmetic mean of the three seasonal poverty indices; that is, AP=$(P_1 + P_2 + P_3)/3$. Chronic poverty (CP) is the obtained poverty measure applied to the annual living standard. CP corresponds to a situation where households could have smoothed their consumption if they had desired (Muller, 2008). Transient poverty (TP), over the studied agricultural year, is residual poverty after chronic poverty is taken into account in annual poverty: TP= AP- CP.

All these poverty estimators are estimated alternatively using the minimum and maximum prices faced by each household. 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 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[8]. Finally, it is useful to note that agropastoral households are far from being the poorest in Niger, as noted, for example, in Gueye et al. (2007)

1.4 Results

1.4.1 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 Prydz, 2016). This poverty line is equivalent to \$3.08 per adult

[8]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.

equivalent per day in our case[9] 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 1.2: 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)		
	FGT0	FGT1	FGT2	FGT0	FGT1	FGT2	FGT0	FGT1	FGT2	FGT0	FGT1	FGT2
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

Notes: 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. FGT0 is the poverty head-count ratio, FGT1 is the poverty gap index and FGT2 is the poverty severity index.

As seen in Table 1.2, the poverty estimates obtained using the two types of food prices are significantly different. The estimated sampling errors account for the 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 differ-

[9]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: World Bank accessed on March 14, 2020).

ences 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.

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

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.

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.

1.4.2.1 Absolute poverty lines

The absolute poverty lines are estimated using the cost-of-basic-needs method (see the Section 3 of the Appendix for details). Table 11 in Section 5 of the 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.

1.4.2.2 Seasonal poverty

The results of the seasonal poverty estimates are presented in Table 1.3[10]. For all three seasons, the two seasonal poverty estimates with alternative prices are significant at the 1 percent level. Also, the difference between these two seasonal poverty estimates are significant in 37 per cent of all the cases.

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 1.3), the impact of using minimum prices versus maximum prices is more pronounced for the South and the country as a whole than for the North. During this season, the poverty rate varies from 29.1 to 32.1 percent, while poverty intensity and poverty severity range from 11.6 to 16.7 percent and from 6 to 11 percent, respectively, depending on the region and the use of alternative prices. Moreover, the differences in the poverty estimates between the North and the South are larger when they are assessed with minimum prices than maximum prices.

[10]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 1.3: 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											
	FGT0	FGT1	FGT2	FGT0	FGT1	FGT2	FGT0	FGT1	FGT2	FGT0	FGT1	FGT2
Using maximum food prices	.306***	.144***	.088***	.291***	.118***	.061***	.315***	.162***	.107***	-.024	-.043	-.046
	(.069)	(.036)	(.024)	(.073)	(.037)	(.022)	(.107)	(.056)	(.038)	(.140)	(.073)	(.048)
Using minimum food prices	.310***	.146***	.090***	.293***	.116***	.060***	.321***	.167***	.111***	-.028	-.050	-.051
	(.069)	(.037)	(.024)	(.073)	(.037)	(.022)	(.107)	(.058)	(.039)	(.140)	(.075)	(.050)
Differences	-.004**	-.002**	-.002**	-.002	.002**	.001	-.006**	-.005***	-.004**	.004	.007**	.005***
	(.002)	(.001)	(.001)	(.002)	(.001)	(.001)	(.003)	(.002)	(.002)	(.004)	(.003)	(.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***	.136***	.083***	.277***	.103***	.053***	.335***	.159***	.104***	-.057	-.055	-.050
	(.064)	(.032)	(.022)	(.078)	(.034)	(.020)	(.095)	(.050)	(.035)	(.130)	(.065)	(.045)
Using minimum food prices	.307***	.136***	.083***	.292***	.102***	.052***	.317***	.160***	.104***	-.025	-.058	-.052
	(.061)	(.032)	(.022)	(.077)	(.033)	(.019)	(.089)	(.050)	(.035)	(.124)	(.064)	(.044)
Differences	.005	.000	.000	-.014	.001	.001	.018	-.001	.000	-.032**	.003	.002**
	(.007)	(.001)	(.001)	(.010)	(.002)	(.001)	(.010)	(.001)	(.001)	(.015)	(.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***	.157***	.102***	.317***	.116***	.066***	.342***	.185***	.126***	-.025	-.069	-.060
	(.064)	(.036)	(.025)	(.072)	(.035)	(.022)	(.098)	(.057)	(.040)	(.130)	(.073)	(.051)
Using minimum food prices	.337***	.157***	.101***	.343***	.120***	.067***	.333***	.182***	.124***	.01	-.062	-.057
	(.063)	(.036)	(.026)	(.065)	(.034)	(.022)	(.098)	(.057)	(.041)	(.127)	(.073)	(.051)
Differences	-.005	.000	.001	-.026	-.004**	-.001	.009**	.003*	.002	-.035*	-.007**	-.003
	(.009)	(.002)	(.001)	(.020)	(.002)	(.001)	(.005)	(.002)	(.002)	(.018)	(.003)	(.003)
Relative difference	-.015	.000	.009	-.075	-.033	-.015	.027	.016	.016	-3.5	.11	.053

Notes: 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 1.3) are generally similar to those obtained for the cold and dry season. The poverty rate extends from 27.7 to 33.5 percent, while poverty severity and the poverty gap vary from 0.05 to 0.10 and from 0.10 to 0.16 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 headcount 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.

1.4.2.3 Annual, chronic, and transient poverty

As previously mentioned, the annual poverty measures are defined as the arithmetic means of the seasonal poverty measures. Table 1.4 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 intensity, 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 1.4: Annual, Chronic and Transient Poverty indices 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											
	FGT0	FGT1	FGT2	FGT0	FGT1	FGT2	FGT0	FGT1	FGT2	FGT0	FGT1	FGT2
Using maximum food prices	.317***	.146***	.091***	.295***	.113***	.060***	.331***	.168***	.112***	-.036	-.056	-.052
	(.065)	(.034)	(.023)	(.073)	(.035)	(.021)	(.099)	(.054)	(.037)	(.132)	(.070)	(.047)
Using minimum food prices	.318***	.147***	.091***	.309***	.113***	.060***	.324***	.169***	.113***	-.014	-.057	-.053
	(.063)	(.035)	(.024)	(.070)	(.034)	(.020)	(.097)	(.055)	(.038)	(.128)	(.070)	(.048)
Differences	-.001	-.001	.000	-.014*	.000	.000	.007*	-.001	-.001	-.021***	.001	.001
	(.004)	(.001)	(.001)	(.007)	(.001)	(.001)	(.004)	(.001)	(.001)	(.008)	(.002)	(.002)
Relative difference	-.003	-.006	.000	-.045	.000	.000	.021	-.006	-.009	1.5	-.017	-.019
	Chronic Poverty											
Using maximum food prices	.265***	.112***	.063***	.270***	.095***	.044***	.262***	.123***	.076***	.007	-.028	-.032
	(.052)	(.027)	(.018)	(.070)	(.031)	(.017)	(.075)	(.041)	(.028)	(.106)	(.055)	(.036)
Using minimum food prices	.273***	.109***	.061***	.270***	.098***	.047***	.275***	.117***	.070***	-.005	-.018	-.023
	(.048)	(.026)	(.017)	(.069)	(.032)	(.018)	(.066)	(.039)	(.026)	(.097)	(.053)	(.034)
Differences	-.008	.003	.002**	.000	-.003	-.003***	-.013	.006***	.006***	.013	-.009***	-.009***
	(.010)	(.002)	(.001)	(.012)	(.002)	(.001)	(.014)	(.002)	(.002)	(.019)	(.003)	(.003)
Relative difference	-.029	.027	.033	.000	-.03	-.064	-.047	.051	.085	-2.6	.5	.39
	Transient Poverty											
Using maximum food prices	.051	.034*	.028**	.025	.017	.015	.068**	.045***	.036***	-.043	-.028	-.020
	(.032)	(.018)	(.012)	(.064)	(.040)	(.025)	(.031)	(.016)	(.012)	(.066)	(.039)	(.026)
Using minimum food prices	.044	.037**	.030**	.038	.014	.012	.048	.052***	.042***	-.009	-.038	-.030
	(.035)	(.020)	(.014)	(.068)	(.040)	(.025)	(.037)	(.020)	(.015)	(.073)	(.042)	(.028)
Differences	.007	-.003	-.003	-.013	.003	.003	.020	-.007**	-.006**	-.034*	.010***	.010***
	(.011)	(.002)	(.002)	(.014)	(.002)	(.002)	(.013)	(.003)	(.003)	(.020)	(.004)	(.003)
Relative difference	.16	-.081	-.10	-.34	.21	.25	.42	-.13	-.14	3.78	-.26	-.33

Notes: 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 1.4 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 agro-pastoral 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 and Banque Mondiale, 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 higher in the South when using minimum or maximum prices.

Table 1.5: Percentage of Transient Poverty in Annual Poverty

	National (N=671)			North (N=284)			South (N=387)			Difference between the North and the South		
	FGT0	FGT1	FGT2	FGT0	FGT1	FGT2	FGT0	FGT1	FGT2	FGT0	FGT1	FGT2
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 1.4 and 1.5 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 transient poverty rate (poverty severity) ranges from 2.5 percent in the North to 6.8 percent in the South (1.2 per cent and 4.2 per cent). 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.

1.5 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 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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Chapter 2

Predicting Resilience against Poverty with Machine Learning: Evidence from Nigeria

2.1 Introduction

The use of machine learning (ML) algorithms in economics and public policy studies is spreading rapidly(Athey, 2018; Athey and Imbens, 2019; Mullainathan and Spiess, 2017; McBride et al., 2021). They are mainly used for their predictive performance to tackle the so-called "prediction policy problems" (Kleinberg et al., 2015). In development economics, a growing empirical work has tested the potential of ML in predicting and mapping poverty (Jean et al., 2016; Browne et al., 2021; McBride and Nichols, 2018; Li et al., 2022; Aiken et al., 2022). These studies highlight the potential of these tools to accurately predict well-being measures and identify the poor, which help improve the targeting performance of development programs. In predicting the well-being measures, most of these predictive tools focus on predicting a point estimate and do not give any uncertainty related to their prediction.

A strand of ML literature highlights the importance of assessing the uncertainty of any prediction and advocates not just predicting a single estimate but rather an entire conditional probability density function. ML tools have been used to estimate conditional probability density function mainly in finance (Rothfuss et al., 2019), insurance (Delong et al., 2021), and economics (Wick et al., 2021). Predicting the conditional probability density function of a household's or individual's well-being measures has two main advantages: not only does this allow us to quantify the uncertainty linked to a prediction, but it also allows us to generate other statistics than the conditional mean, such as the median and quantiles, which will help to understand better the stochastic nature of the welfare measures in an individualized manner.

In addition to poverty, the most debated notion among development practitioners, resilience and vulnerability, begins by arousing interest. Indeed, the main interest in these two notions lies in the fact that development and humanitarian agencies want to be able to put in place actions to prevent households from falling into poverty.

The theoretical foundation and the empirical methodologies of the measurement of resilience have been validated by researchers in several scientific articles[1] belonging to a strand of research called "development resilience." For example, Barrett and Constas (2014) proposed one of the main conceptualizations of development resilience found in the literature[2], where *resilience* is defined as a normative condition, that is a probability of remaining above some minimal standard of living conditionally of some observable characteristics and exposure to shocks. This conceptualization is probabilistic *ex-ante* well-being dynamic and draws together the methods and theories related to poverty trap and vulnerability. Under this conceptualization,

[1]Cissé and Barrett (2018); d'Errico and Di Giuseppe (2018); d'Errico et al. (2020) among many others.

[2]In their recent review of the literature devoted to the definition and measurement of development resilience, Barrett et al. (2021) distinguished two other main conceptualizations: (i) resilience as a capacity "that ensures stressors and shocks do not have long-lasting development consequences" (Constas et al., 2014) and is captured by a multidimensional latent variable combining observable and unobservable features, and (ii) resilience defined as a return to equilibrium, i.e., the capacity to recover from a shock experienced on a well-being outcome, focusing on its the ex-post effect.

a person, household, or other aggregate unit is resilient if and only if its capacity to avoid poverty in the face of various stressors and the wake of myriad shocks remains high over time.

This paper will use this definition of resilience as a normative condition proposed by Barrett and Constas (2014). Based on this conceptualization, Cissé and Barrett (2018) proposed a measure of resilience using a conditional moment approach. Under this approach, a sequence of two regressions (ordinary least square (OLS) or a generalized linear model (GLM)) is estimated to generate the first moment (conditional mean) and the second moment (conditional variance) of a household's well-being distribution conditionally to its observable characteristics and exposure to shocks. With these two moments and an assumed distribution, a household's well-being probability density function can be generated, from which a probability of being above a pre-specified threshold can then be estimated. This conditional probability represents the resilience score.

In order to set up an early warning system for the fight against poverty sustainably, policymakers have some interest in identifying non-resilient households. They also want to quantify the effort required to build and strengthen the capacity of non-resilient households to cope with different types of shocks while maintaining their standard of living above the poverty line. For this purpose, there is a need to have a measure that can achieve these goals. The resilience measure proposed by Cissé and Barrett (2018) aims to fulfill these objectives. Indeed, this probability score can be used as an indicator to quantify the prevalence of resilient or non-resilient households in a population by using a probability threshold. Also, it can be used as an outcome in the impact analysis of policies aimed at strengthening and building household resilience capacities.

The econometric technique proposed by Cissé and Barrett (2018) to construct household-specific resilience scores is beginning to be widely used by academic researchers in several contexts, specifically for impact evaluation (Upton et al., 2016; Knippenberg et al., 2019; Phadera et al., 2019; Premand and Stoeffler, 2020). Indeed, it is simple to implement and allows the estimation of an outcome that characterizes the level of resilience of a household. This outcome is then used in an impact evaluation strategy to assess the effectiveness of development policies or programs in building a household's resilience. For example, Phadera et al. (2019) employ this technique to construct household-specific resilience scores, which are then used as an outcome to estimate the impact of an asset transfer program on household resilience in rural Zambia.

However, despite its appeal, this technique to measure resilience have some limitations in its ability to accurately predict outcome out-of-sample (Barrett et al., 2021). Indeed, Upton et al. (2022) show that Cissé and Barrett (2018) approach to measuring resilience suffers from a high rate of both false positive and false negative. ML models can, in principle, accomplish this task since they are built to excel in predicting outcomes (Varian, 2014).

This paper is at the intersection between the strand of research related to the potential of ML in predicting probability density function and the stand of the research related to the measure of development resilience defined as a normative condition as proposed by Cissé and Barrett (2018). By combining these two strands of research, this paper, proposes a strategy to predict a household's development resilience using ML. The proposed strategy combines a Gaussian Mixture Model (GMM) and a Neural Network (NN) to predict household-specific conditional well-being probability density function. Combining a GMM and a NN in our approach allows us to benefit from their strengths in predicting households' resilience scores. Indeed, GMMs can theoretically approximate any smooth probability density function (Goodfellow et al., 2016, p. 65), while NNs are known for their flexibility, that is, their ability to approximate arbitrarily well any function (Hornik et al., 1989). In this strategy, a NN is used to predict the parameters (mixing coefficients, mean, and variance of each component, i.e., the Gaussian distribution) of the GMM. Bishop (1994) called this combination of GMM with NN a "mixture density network" and shows that it can approximate any probability density function to arbitrary accuracy.

Our strategy to predict resilience is similar to the approach proposed by Cissé and Barrett (2018): both are rooted in the conceptualization of development resilience proposed by Barrett and Constas (2014). However, they differ significantly in how the household well-being conditional probability density functions are estimated and predicted. With the conditional probability density function, one can generate the predicted resilience score as the probability of being above a pre-specified threshold.

Moreover, this paper goes beyond the standard ML tools used in development economics to predict a point estimate of well-being measures by predicting its conditional probability density function.

Recently, two papers have investigated how ML methods can be used to predicting resilience, e.g., the contribution by Knippenberg et al. (2019) and, Garbero and Letta (2022). In the first paper, the authors applied two ML techniques: least absolute shrinkage and selection operator (LASSO) and random forest to predict resilience measured as the Coping Strategy Index of Malawian households. While in the second paper, Garbero and Letta (2022), by using a unique cross-country sample from 10 impact evaluations of development projects, test the out-of-sample performance of ML tools in predicting non-resilient households, where resilience is subjective and defined as the perceived ability to recover from shocks. In both papers, the authors used a predefined metric of resilience before applying the ML algorithm for the prediction task.

We build on these pioneering works by providing evidence on how resilience can be measured and predicted. Moreover, and importantly, we are interested in accurately predicting the conditional probability density function, which will endorse the quality of the resilience prediction.

The proposed approach is tested on household data from Nigeria, and the results showed that:

1. Our approach performed well in predicting household conditional probability

density function compared to the sequence of two regressions proposed by Cissé and Barrett (2018), which serve as a benchmark,

2. Not correctly predicting the conditional probability density has consequences on the quality of the predicted resilience scores, which in this case are overestimated,

3. As the benchmark, our approach orders similarly the households based on their resilience score,

4. The out-of-sample prediction and targeting performances of our approach are better than that of the benchmark.

The results shed light on ML's potential, particularly our approach, to accurately predict household resilience through a correct prediction of its conditional probability density function. They also showed that not accurately predicting the probability density function may lead to overestimating the predicted resilience score, which has implications for quantifying the prevalence of resilience in a population and the amount of effort needed to build resilience.

The rest of this paper is organized as follows. Section 2 presents the methods used to predict resilience and assess this prediction's quality. Section 3 describes the data on which the proposed approach is tested. Finally, section 4 reports the results of the empirical analysis, and section 5 concludes.

2.2 Methods

2.2.1 Measuring resilience as a normative condition

This paper follows Barrett and Constas (2014) conceptualization of development resilience: "the capacity over time of a person, household or other aggregate units to avoid poverty in the face of various stressors and the wake of myriad shocks. If and only if that capacity is and remains high over time, then the unit is resilient." It is built on the theories of vulnerability and poverty trap and allows integration of their distinctive strength.

Like the concept of vulnerability[3], the development resilience is a probabilistic ex-ante measure, but with two crucial differences. First, while resilience focuses on the long-term impacts of shocks and stressors, vulnerability is mainly concerned with the immediate impact of shocks and does not account for exposure to stressors (Phadera et al., 2019). Second, unlike vulnerability, whose emphasis on the immediate impact of shocks overlooks welfare path dynamics, resilience accounts for well-being dynamics and allows the possibility of nonlinear path dynamics (Cissé and Barrett, 2018; Phadera et al., 2019). Allowing for potentially nonlinear path dynamics can accommodate the nonlinear persistence of shocks, which is essential to

[3]In economics, the concept of vulnerability refers to a probabilistic ex-ante measure of the likelihood that future consumption will fall below a poverty threshold (Calvo and Dercon, 2007; Ligon and Schechter, 2003)

identifying potentially heterogenous wealth-dependent responses to shocks (Cissé and Barrett, 2018).

Barrett and Constas (2014) represent resilience using a conditional moment function of well-being, $m_i^k(y_{i,t+s}|y_{i,t}, X_{i,t+s}, \varepsilon_{i,t+s})$, where m^k is the k^{th} moment of household i's well-being, y, in period $t+s$ (with $s>0$); with resilience a function of well-being y_t, a household and community level covariates X and random disturbances ε.

In the poverty trap literature, a deterministic relationship between $y_{i,t}$ and $y_{i,t+s}$ is generally employed, but here, it is replaced by a conditional moment growth function and related conditional dynamic transitional distribution functions (Phadera et al., 2019; Cissé and Barrett, 2018).

Barrett and Constas (2014) conceptualization of resilience is relevant in the cases of both multiple equilibria and single equilibrium poverty traps. It applies to non-linear path dynamics with multiple steady-state equilibria and a single steady-state equilibrium below the poverty line. In the case of multiple steady-state equilibria, resilience is measured as the cumulative probability above the dynamic poverty threshold; and as the cumulative probability above the static poverty threshold $\overline{y}$, in the case of a single steady-state equilibrium. Therefore, for a household to be more resilient, less of its well-being probability distribution function should fall below the poverty line. This probability distribution function depends on its well-being level at time t and the dispersion in the distribution of the outcome.

Cissé and Barrett (2018) operationalize Barrett and Constas's (2014) conceptualization of resilience with an econometric approach, which can be summarized in two steps. In the first step, a regular Ordinary Least Square (OLS) regression estimates the household-specific conditional mean, the first moment, of well-being $y_{i,t}$.

$$y_{i,t} = \sum_k \beta_k y_{i,t-1}^k + \gamma x_{i,t} + \lambda s_{i,t} + \varepsilon_{i,t}, \tag{2.1}$$

where the subscript k represents a polynomial order (e.g., 2 for quadratic and 3 for cubic) and allows for S-shaped dynamics that are typical of multiple equilibria poverty traps, with $k=3$ its most parsimonious parametric specification (Barrett et al., 2016).

In equation 2.1, $x_{i,t}$ represents household's or community characteristics, while $s_{i,t}$ represents the shocks and stressors they faced individually or at the community level.

In the second stage and under the mean zero residuals condition, the residuals from equation 2.1 are calculated, squared, and used in a second regression[4] to estimate the household-specific conditional variance (the second moment) of well-being using the same explanatory variables as in the first step.

[4]The second equation is fitted by a generalized linear model, particularly a Poisson model (log-linear).

$$\varepsilon_{i,t}^2 = \sum_k \delta_k y_{i,t-1}^k + \nu x_{i,t} + \vartheta s_{i,t} + \omega_{i,t} \tag{2.2}$$

With these two conditional moments, and an assumed distribution (a log normal distribution in our case), a household-specific conditional probability density function can be generated. From this household-specific conditional probability density function, one can estimate the complement of the cumulative distribution function (CDF) above the poverty line, which gives a probability score, the resilience score.

The resilience score $\rho_{i,t}$ of a household i at time t is defined as :

$$\rho_{i,t} = \Pr(y_{i,t} > \overline{y} | y_{i,t-1}, x_{i,t}, s_{i,t}) = 1 - F_{y_{i,t}}(\overline{y}), \tag{2.3}$$

where $F(.)$ is the assumed cumulative distribution function estimated with the mean and variance predicted from equations 2.1 and 2.2, respectively.

This two sequence of regressions approach proposed by Cissé and Barrett (2018) is appealing by its simplicity to be implemented. However, it suffers from some limitations, particularly its ability to predict well-being out-of-sample, a limitation shared by the most common resilience measurement approach (Barrett et al., 2021; Upton et al., 2022). Can this be explained by the arbitrary choice of the type of well-being distribution or the less flexible form of equations 2.1 and 2.2 to estimate household-specific well-being distribution? Since predicting a household-specific resilience against poverty, in the spirit of Barrett and Constas's (2014) conceptualization of resilience, amounts to predicting its well-being's conditional probability density function.

In this paper, we propose a more flexible approach to overcome the out-of-sample prediction limitations. The proposed approach combines Mixture Models, notably a Gaussian Mixture Model, with a Neural Network to predict household-specific well-being conditional density function and thus its resilience score. Its performance will be compared to the method proposed by Cissé and Barrett (2018), which we will call the standard "C&B" approach or the "OLS & GLM" approach. The following section describes in detail the proposed approach.

2.2.2 Combining mixture density models with neural networks to predict resilience

The approach proposed in this paper is made of two components: a mixture density model and a neural network. We emphasize that none of these components or their integration is original, but the novelty here lies in their application to predict a household's resilience, as conceptualized by Barrett and Constas (2014). In the ML literature, since Bishop (1994), this approach has been already applied with success to financial (Rothfuss et al., 2019), insurance (Delong et al., 2021), and meteorological data sets (Cornford et al., 1999; Carney et al., 2005). Bishop (1994), in his work, called this approach of combining mixture density models with neural networks: "Mixture Density Network (MDN)" and shows that it could better describe the conditional distribution of multimodal, inverse problem, and Brownian processes. In the rest of the paper, to refer to this approach, we will henceforth use the term "MDN" for simplicity, especially when we want to compare it with the approach described in the previous section. Describing the two components of the proposed approach, "MDN," is essential to understanding how it is constructed and works.

A Mixture Model represents a probability distribution model built from a weighted sum of more simple distributions. Formally, we consider a one-dimensional distribution with m mixture components. It models a probability density function (PDF) *p(y)* as a mixture of m PDFs indexed by j $p_j(y)$, with weights, $\prod = \{\alpha_0, \alpha_1, ..., \alpha_{m-1}\}$, where $\sum_{j=0}^{m-1} \alpha_j = 1$, by the following equation:

$$p(y) = \sum_{j=0}^{m-1} \alpha_j p_j(y|\theta_j) \tag{2.4}$$

where θ_j are the distribution parameters describing the shape and location of the distribution. In equation 2.4, p_j can be seen as a kernel and could be any parametrized distribution.

Bishop (1994) uses a Gaussian kernel to build "MDNs" in his work. He argues that, with this choice, any probability density function can be approximated to arbitrary accuracy, provided that the mixing coefficients and the Gaussian parameters (mean and variance) are correctly chosen. We follow this line in our work and rely on the universal approximator of densities property of the Gaussian Mixture Model (GMM) in constructing "MDNs" (Goodfellow et al., 2016, p. 65).

By using a Gaussian kernel, the equation 2.4 becomes :

$$p(y|\Pi,\Theta) \; = \sum_{j=0}^{m-1} \alpha_j \frac{1}{\sqrt{2\pi\sigma_j^2}} \exp(\frac{-1}{2\sigma_j^2}(y-\mu_j)^2) \tag{2.5}$$

Where μ_j and σ_j^2 are the mean and the variance of distribution j, respectively, and α_j the mixing coefficient of Gaussian distributions.

The corresponding likelihood is calculated as follows (assuming independence) for n data points:

$$l(X|\Pi,\Theta) = \prod_{i=0}^{n-1} \left[\sum_{j=0}^{m-1} \pi_j p_j(x_i|\theta_j) \right] \tag{2.6}$$

From equation 2.5, the conditional probability density function can be expressed as follows:

$$p(y|\mathbf{x}) = \sum_{j=0}^{m-1} \alpha_j(\mathbf{x}) \frac{1}{\sqrt{2\pi\sigma_j^2(\mathbf{x})}} \exp(\frac{-1}{2\sigma_j^2(\mathbf{x})}(y-\mu_j(\mathbf{x}))^2) \tag{2.7}$$

In equation 2.7, the GMM parameters $(\alpha_j, \mu_j, \sigma_j)$ are conditioned on the input $\mathbf{x}$, the same as the explanatory variables used in equations 2.1 and 2.2 of the econometric approach proposed by Cissé and Barrett (2018).

A Neural Network (NN) will be used to predict the GMM parameters in equation 2.7, conditioned on the input $\mathbf{x}$. Neural Networks are known for their flexibility and ability to arbitrarily approximate any function (Hornik et al., 1989). In our case, a single Neural Network is used to find the function that better maps input $\mathbf{x}$ to the three GMM parameters simultaneously. For this purpose, the NN needs to minimize a loss function: the Negative Log-Likelihood, which is equivalent to maximizing the likelihood function of equation 2.6.

$$f(X|\Pi,\Theta) = -\sum_{i=0}^{n-1} \log(\sum_{j=0}^{m-1} \pi_j p_j(\mathbf{x}_i|\theta_j)) \tag{2.8}$$

The loss function f is a differentiable function provided that p_j is differentiable with respect to θ_j. Thus, standard techniques based on stochastic gradient descent can be applied to optimize the network weights with respect to this loss function.

During the estimation, the inputs $\mathbf{x}$ are passed through several hidden layers within the NN to produce the normalized neurons representing the parameter needed to construct the mixture of distributions. During this last stage of normalization, some restrictions are imposed on the Gaussian distribution parameters : (i) weights, the mixing coefficients, are probabilities and therefore should be less than one and sum to unity, (ii) and the shape parameter, the variance, should be positive (see the section B3 of the Appendix for more details on how the NN is trained).

With the three parameters $(\hat{\alpha}_j, \hat{\mu}_j, \hat{\sigma}_j)$ of GMM, outputs of the NN, one can predict, for each household i at time t, its well-being conditional density function, $\hat{p}(y_{i,t}|\mathbf{x})$ (see equation 2.7), which is a mixture of Gaussian distribution. The corresponding cumulative distribution function, at time t, of its well-being evaluated at the poverty line $\overline{y}$, is given by the following formulae :

$$F_Y(\overline{y}) = \sum_{j=0}^{m-1} \hat{\alpha}_j \hat{F}_j(\overline{y}), \tag{2.9}$$

where, and for each household i at time t, m represents the number of components of the mixture of Gaussian distributions, $\hat{\alpha}_j$ the weight of the j^{th} components predicted by the NN and $\hat{F}_j(\overline{y})$ it's cumulative distribution function evaluated at the poverty line $\overline{y}$. $\hat{F}_j(\overline{y})$ is estimated from the outputs $(\hat{\alpha}_j, \hat{\mu}_j, \hat{\sigma}_j)$ of the NN.

Therefore, the household predicted resilience score is the complement of the cumulative distribution function defined in equation 2.9.

2.2.3 Evaluation of the predicted resilience score

2.2.3.1 Evaluating the accuracy of the predicted well-being probability density functions

Evaluating the predicted resilience scores amount to evaluate the predicted probability density functions (PDFs) on the test data[5], the last round of the survey data, as the latter is used to compute the former. However, assessing the predicted PDFs' accuracy is challenging because the predictions take the form of probability distributions, whereas the observations are real-valued. To overcome this challenge, Diebold et al. (1998) and Diebold et al. (1999) proposed to use the probability integral transforms (PITs), one of the main approaches used to assess the quality of univariate and multivariate density forecasts in the literature (Rossi, 2014; Rossi and Sekhposyan, 2019; Caselli et al., 2020; Wick et al., 2021, among others).

A PIT is a cumulative probability evaluated at the target variable's actual realized value. It measures the likelihood of observing a value less than the actual realized value, where the probability is measured by a density forecast (Rossi, 2014).

Diebold et al. (1998) demonstrated that PIT values are uniform, independent, and identically distributed for correctly specified density forecasts. We will follow this line in our work and use PIT to assess the accuracy of the predicted household-specific well-being probability density function. For a household i, and using its predicted PDFs and its actual realized value of well-being, its PIT value z_i is calculated, in the test set, as follows :

$$z_i = P(y \leq y_i) = \int_{-\infty}^{y_i} \hat{p}_i(y')dy', \tag{2.10}$$

where y_i is the actual realized values observed of its well-being, and $\hat{p}_i(.)$ its predicted well-being PDF. For a given household, z_i represents its probability of having a level of well-being smaller than its actual realized observed level of well-being, based on its predicted PDF. According to Diebold et al. (1998), all the z_i values in the test set should be uniform, independent, and identically distributed if the predicted PDFs are accurate. The uniformity property means that the probability that the realized well-being value is higher (lower) than the predicted well-being value is the same regardless of whether one considers high realizations or low realizations of well-being (Rossi, 2014). Therefore, beyond assessing the loss function (i.e., minimizing the negative log-likelihood), a test of the correctness of the predicted household-specific well-being distribution function involves comparing the empirical distribution of PIT values to the theoretical uniform distribution between 0 and 1. This comparison is performed with four methods: three qualitative and one quantitative.

The three qualitative methods to compare the PIT values distribution to the theoretical uniform distribution between 0 and 1 are mainly graphical visualizations.

[5]See Section B3 of the appendix for details on how the data are split into train set and test set when training the Neural Network to estimate the three parameters of the GMM. The training set is composed of all-but-last survey rounds data.

First, we plot the histogram of PIT values and assess visually if it exhibits a distinct picture from a uniform distribution. Second, we perform a Q-Q plot of the PIT values' empirical distribution. If the PIT values have a uniform distribution, the Q-Q plot should be close to the 45-degree line.

The third qualitative method, the inverse quantile profile plot, proposed by Wick et al. (2021) is a refinement of the first one and allows us to assess the correctness of the overall shape of the household-specific well-being PDF. It also helps us judge whether, for example, the distribution's tails describing the rare situation for the household are problematic.

In this third method, the PIT values are compared with specified quantiles (q), defined as the inverse of a cumulative density function. For example, with this method, one can assess if the distribution's median (i.e., q=0.5) is correctly predicted by the "MDN" or the "OLS & GLM" models. For this purpose, the household's specific PIT values are compared to the value of 0.5, and the ratio of PIT values being lower/higher than 0.5 is computed. This ratio should be very close to 0.5 in the case of the median; 50 percent of the observed level of well-being should be below the median of the corresponding individually predicted PDF and 50 percent above. Following Wick et al. (2021), this process is repeated for a range of quantiles (q=0.1, q=0.3, q=0.5, q=0.7, q=0.9, and q=0.97). Doing so allows us to assess the correctness of the overall shape of the predicted household-specific well-being distributions.

Contrary to the histogram of PIT values, the inverse quantile profile plots do not work on household-specific PDF prediction but require a statistical population to compute the ratio of PIT values above or below a specified quantile value. These ratios can be computed over all the records in the test sample. However, Wick et al. (2021) argued that certain deficiencies for a subset of households (those living in a particular area, or involved in a specific activity, for example) might not be revealed. Therefore, the inverse quantile profile plot should be conditioned to any variable used during the training, which will help us see whether the incorrectness of the predicted PDFs is related to some observable variables, such as household characteristics.

In addition to these qualitative methods, a quantitative method measuring the difference between two probability distributions is used to compare the PIT values distribution with the expected uniform distribution. In the literature, several approaches are proposed to quantify the difference between two probability distributions: the *first Wasserstein distance*, known as earth mover distance (EMD); the *Kullbacker-Leibler divergence*, known as relative entropy; the *Jensen-Shannon divergence*, known as information radius (Wick et al., 2021). Between these three approaches, the *first Wasserstein distance* is known to be the one more sensitive to minor deviations because of its linear behavior around zero (Wick et al., 2021).

The *first Wasserstein distance* represents the symmetric distance between two PDFs on a given metric space, and following Wick et al. (2021), we focus on this distance, which can be defined by:

$$EMD(P,Q) = \frac{\sum_{k=1}^{N} |F_P(x_k) - F_Q(x_k)|}{N}, \tag{2.11}$$

where $F_P(X)$ and $F_Q(X)$ are the CDFs of the two PDFs $P(X)$and $Q(X)$respectively, and x_k represents the average value of X in bin k, and $N$the total number of bins of X. From the *first Wasserstein distance*, Wick et al. (2021) proposed an accuracy[6] measure for the predicted PDFs in the range (0,1) defined by :

$$accuracy = 1 - 2 * EMD \tag{2.12}$$

We use these three methods to compare the performance of the "MDN" and "OLS & GLM" approach in predicting household-specific well-being probability density function.

2.2.3.2 Evaluating the predicted resilience score

The predicted household-specific resilience score is obtained as the complement of the cumulative distribution function above the poverty line of its predicted well-being PDF. The evaluation of the predicted resilience score is based on comparative statistical methods to assess its correspondence with the measure of well-being. These methods also compare the predicted household's resilience score from "MDN" to those from "OLS & GLM."

Following Upton et al. (2022), we used three different methods to compare the predicted household's resilience score from the two models and their correspondence to the measure of well-being.

We first compared the kernel density estimates of the distributions of household-specific resilience scores predicted by each model. A Kolmogorov-Smirnov test (KS-test) is used for this comparison. The KS-test is based on comparing two CDFs to find the maximum distance between them. It is sensitive to any differences in the two distributions and therefore is suited to compare their overall shape. Comparing the distributions of resilience scores predicted from the two models will help us understand how they may influence the prevalence of resilience among households and the magnitude of change needed to "build resilience" (Upton et al., 2022).

The second comparison of interest is whether the predicted measure of resilience from the two models ranks households differently from the least to most resilient. This ranking has implications for targeting interventions toward the least or most resilient households. For this purpose, the Spearman rank correlation coefficients are computed between the predicted resilience scores from the two models and the measure of well-being. The Spearman rank correlation belongs to the family of Rank correlations. This family of non-parametric technics quantifies the association between variables using the ordinal relationship between the values rather than the specific values. The Spearman rank correlation quantifies how a monotonic function associates ranked variables. We also used Kendall's rank correlation to calculate

[6] The maximum value of the first Wasserstein distance is 0.5. An accuracy value of 1 indicates a perfect agreement between both PDFs.

a normalized score for the number of matching or concordant rankings between the predicted scores from the two models and the well-being measure. Compared to the Spearman rank correlation, Kendall's rank correlation usually has smaller coefficients and is known to handle better the cases of ties ranks (Fredricks and Nelsen, 2007).

One would expect a positive and high-rank coefficient correlation between the predicted resilience scores from the two models because they are based on the same framework, which would indicate that a high-rank resilience score in one model corresponds to a higher ranking in the other. On the contrary, a perfect correlation is not expected between the predicted resilience scores and the measure of well-being, although a reasonably high and positive correlation would be preferred; otherwise, they would be redundant in establishing well-being measures (Upton et al., 2022).

In ranking households regarding their resilience score, one would also be concerned about the correspondence among the two predicted resilience score in ranking the worst off since most poverty alleviating or resilience programming focuses on the poorest or most vulnerable households. Therefore, we analyzed the share of the households ranked in the bottom 20% for one predicted resilience score and the bottom 20% for the other predicted resilience score. Also, for these worst-off households, we compared the magnitude of effort needed to "build their resilience" with the two models.

The final comparison method focused on the performance of the two models in predicting household poverty status by using the predicted resilience status. This comparison will help us judge if the predicted household resilience measure can be used to target poor households, even if they are not conceived for this purpose. Nevertheless, humanitarian and development agencies need to target non-resilient households can result in the use of these resilience scores. The binary predicted household resilience classification is obtained by applying two probability thresholds, one at 0.5 and the other at 0.8, on the predicted resilience score, which leads us to analyze the targeting performance in these two cases.

The predicted household resilience status targeting performance is assessed in the time domain. In the time domain, the objective is to see if knowing today's household's resilience status will help us predict its poverty status in the future. The household resilience status predicted in the last survey round, the test set, as estimated in data from all-but-last survey rounds, the training set, is used to predict its poverty status in the test set. Upton et al. (2022) assess this targeting approach in the time domain, with a bivariate regression of observed well-being outcomes in the last survey wave on the predicted resilience score for the final survey as estimated in data from all-but-final survey waves. The explanatory power of the resilience score in this regression is assessed with the Root Mean Square Error (RMSE).

Assessing this targeting performance in the time domain is crucial since the concept of resilience relies on the stochastic well-being dynamics, so today's household resilience status should indicate its future poverty status. The targeting performance of the two models in the time domain is also compared to the standard and naïve approach, which uses the prior period's household poverty status to predict its poverty status in the next period.

We evaluate the targeting performance for accuracy, precision (positive predictive value), recall (sensitivity), and F1-score (an harmonic mean between recall and precision) in the time domain and for each of the two models.

In order to capture the trade-off between inclusion and exclusion errors for varying the values of the resilience score cut-off thresholds, a receiver operating characteristic (ROC) curve for each model is constructed, and the area under the curve (AUC) is calculated and considered as a measure of targeting quality[7].

2.3 Data

We tested the proposed approach on actual data from Nigeria. These data come from the General Household Survey (GHS) of The World Bank and cover three periods: 2010/211, 2012/2013, and 2015/2016. During each of these three waves, 5,000 households were surveyed in two visits: once during a "post-planting" (PP) period from August to November and a second time from February to April corresponding to the "post-harvest" (PH) period. We then have for each household six rounds of information. The GHS is national and zonal (urban and rural) representative and covers all the 36 states and the Federal Capital Territory (FCT), Abuja.

The survey covered several socio-economics topics, especially those related to households' socio-demographic characteristics, consumption, and the shocks they faced individually or at the community level. However, not all the topics are addressed during the two visits. Some are specific to post-planting or post-harvest periods (e.g., economic shocks and death topics are only addressed in post-harvest visits). Other topics, like education and household assets, are addressed during both visits but only to supplement or update the information collected during the first visit. In addition, information, such as household expenditures, is collected independently and autonomously between the two visits. For this information, we then have complete information at two points in time for each wave.

2.3.1 Outcome variable

Our variable of interest is consumption expenditure, commonly used to measure monetary poverty in developing countries. For each wave, information on total household expenditures is collected independently during the two visits. These expenditures are deflated into real terms, allowing for comparison across households over time and space. They are then normalized by household size.

[7]The accuracy measures the proportion of households correctly classified: those classified as non-resilience and poor and those classified as resilient who are non-poor. The recall measures the proportion of all poor households correctly predicted by their non-resilience status. It is related to the exclusion error, the proportion of resilient households who are poor. Recall = 1- Exclusion error. The precision measures the proportion of non-resilient households who are poor. It is related to the inclusion error, the proportion of non-resilience households who are non-poor. Precision = 1-Inclusion error. The F1-score is the harmonic mean between recall and precision.

Expenditures recorded for each household include both food and non-food expenditures. Food expenses are recorded for 164 different food products (including nine types of meals out of home) based on a recall period of one week, while for non-food products, we have a 1-week recall for four different types, a 1-month for 29 different types, 6-months for 30 types and 12-months for 19 types. The aggregate consumption expenditures are computed for each season and provided with the raw data by The World Bank. Finally, they extrapolated to annual total from the different recall periods.

The total consumption expenditures for each season are converted to the 2016 local currency by adjusting for inflation to account for the temporal variation between the six rounds. From the monthly Consumer Price Index (CPI, base period December 2009) provided by the National Bureau of Statistics (National Bureau of Statistics, 2021), we derived a Consumer Price Index for the corresponding year of the survey[8]. We also account for spatial variation by adjusting the 2016 local currency for inflation between rural and urban areas. Therefore, the total consumption expenditure is converted to the rural and 2016 local currency, and finally to the 2016 Purchasing Power Parity dollars (PPP $) using the 2016 private consumption PPP conversion factor[9].

In order to better analyze welfare dynamics, we constructed, for each round, a balanced sample of 3,432 households from the original sample after removing outliers[10] observations in the household's total expenditure consumption. The household head remains the same in this balanced sample during the six rounds.

In our balanced sample, total real expenditure per capita per day is, on average, generally higher during the PP period compared to the PH period, for each of the three waves, except for the first wave. We also note that the gap observed between the PP and PH periods is more significant in wave three and almost double the gap observed between these two periods in wave two (see sections B1 and B2 of the Appendix). This gap can also be seen in the kernel density of the log of household real total consumption expenditure per capita and per day (see Fig.1). Over the three waves and by period, the outcome variable varies, on average, between 367 and 455 Naira per capita and per day (see sections B1 and B2 of the Appendix).

[8]For example, for wave 1 (2010/211), the first visit (PP period) took place between August and November 2010, and the second visit (PH period) between February and April of 2011. Therefore, to adjust for inflation, we use the CPI data of 2010 for the PP period and the CPI data of 2011 for the PH period.

[9]The PPP conversion data were collected on 05/01/2022 from the website of The World Bank.

[10]Observations that are three standard deviations away from the mean. This criterion is applied to the logarithm of total expenditure.

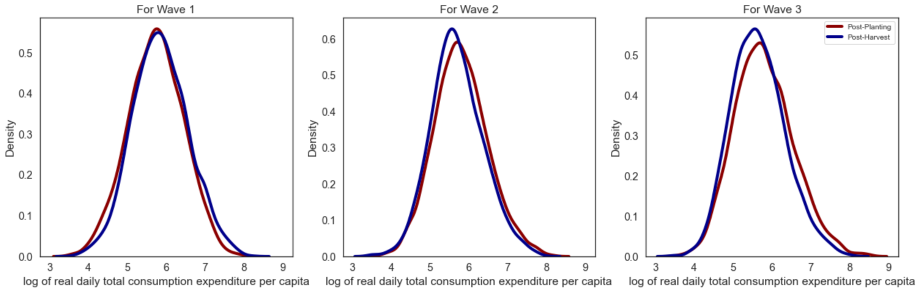

Figure 2.1: Kernel density distribution of the log of household real total consumption expenditure for each of the three waves and by period

In our sample, and using the international poverty line of 1.9 $ PPP per capita and per day, the proportion of poor households varies from 21 percent to 31 percent across waves and periods (see sections B1 and B2 of the Appendix). This proportion also increases with the time from wave 1 to wave 3. However, when using the national poverty line, the percentage of poor households varies from 35 percent to 47 percent, which is, on average, 15 percent higher than the proportions of poor households found with the international poverty line. Therefore, the household resilience scores are predicted using these two poverty lines.

2.3.2 Households covariates

The covariates (see sections B1 and B2 of the Appendix) used as predictors in this paper can be classified into four types: household characteristics, demographics, shocks experienced individually or at the communal level, and dwelling characteristics. These covariates include measures other studies found essential to household well-being, mainly reflecting their long-term welfare status (McBride et al., 2021). These covariates have also been influential in quantifying household resilience (Knippenberg et al., 2019; Vaitla et al., 2020; Upton et al., 2022).

In the balanced sample constructed, on average, 86 percent of households are male-headed, 72 percent live in rural areas, and 60 to 62 percent are married and monogamous. Also, on average, they are mainly involved in agricultural activities.

The household's head age, on average, ranges from 49 to 54 years old, and they have no education or, at most, their education level is limited to the secondary level. These households, on average, live in areas 14 km away from the nearest major road and 68 km away from the nearest market. They are also mainly affected, individually and on average, by a death of an adult working member and an increase in food prices. They are mainly affected by sharp changes in prices and flood events at the community level.

2.4 Results

2.4.1 Evaluating the accuracy of the predicted well-being PDFs

Fig.2.2, presented below, shows the histogram of PIT values according to the qualitative method described in section 2.3.1 for all households in the test set. The predictions of the "MDN" model are compared to the "OLS & GLM," which serve as a benchmark.

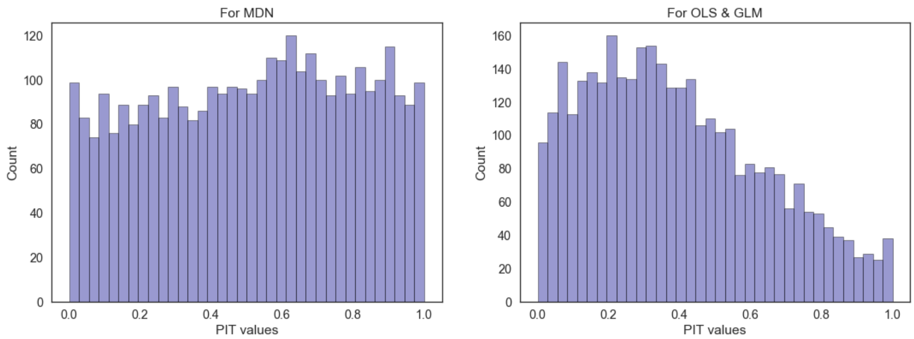

Figure 2.2: Histogram of PIT values to be compared to a uniform distribution for the "MDN" and the "OLS & GLM" models.

The histogram of PIT values of the "MDN" PDF predictions is closer to the uniform distribution, which is expected for optimal PDF predictions, than the histogram of PIT values of the "OLS & GLM" PDF predictions. This result shows our approach's effectiveness in predicting a household's conditional well-being density function using a combination of NN and GMM. For the "OLS & GLM" PDF predictions, the histogram shows a clear pattern of biased central tendencies of PDF predictions (i.e., the histogram is skewed) and a tendency toward overdispersion of PDF predictions (i.e., the histogram has a pattern of inverse-U shape). Furthermore, the histogram of PIT values for the "OLS & GLM" model can also be assimilated to a beta distribution, an apparent deviation from the uniform distribution. The Q-Q plots presented below confirm the deviation from the uniform distribution of the PIT values for the "OLS & GLM" model.

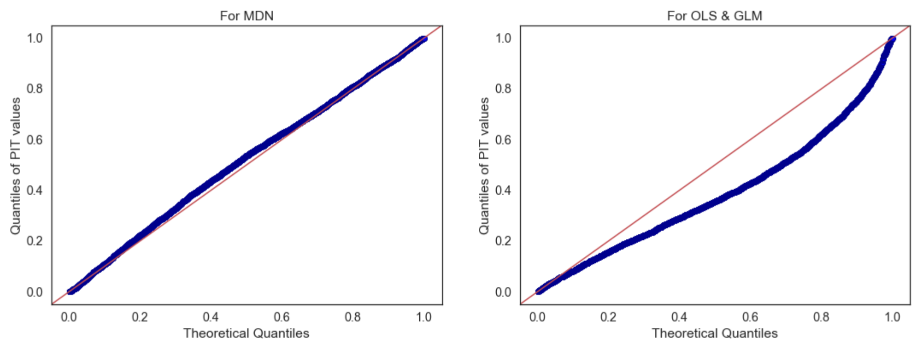

Figure 2.3: Q-Q plots comparing the quantiles of PIT values to the theoretical quantiles of a uniform distribution. These plots are generated using the test set for the "MDN" and the "OLS & GLM" models.

The Q-Q plot of the PIT values for the "OLS & GLM" is distant from the 45-degree line, with a U-shape, a characteristic for right-skewed data distributions (see Fig.2.3). They do not conform with a uniform distribution expected for accurate PDFs predictions. On the contrary, for the "MDN" model, the Q-Q plot shows that the PIT values conform to the uniform distribution.

The predicted PDF's quality can be assessed in detail using the inverse quantile profile plots described in section 2.3.1. The inverse quantile plots' results are presented in Figures 2.4 and 2.5. The dashed horizontal lines in these figures indicate the quantile values, the fraction expected when the predictions are correct. The markers represent the number of observations for which PIT values fall above or below a particular line. If the PDFs are not correctly estimated, the markers will deviate from the horizontal dashed line and their expected values. This visual inspection of markers' position with respect to the dashed horizontal lines will help us judge whether, for example, the distribution's tails describing the rare situation for the household are problematic.

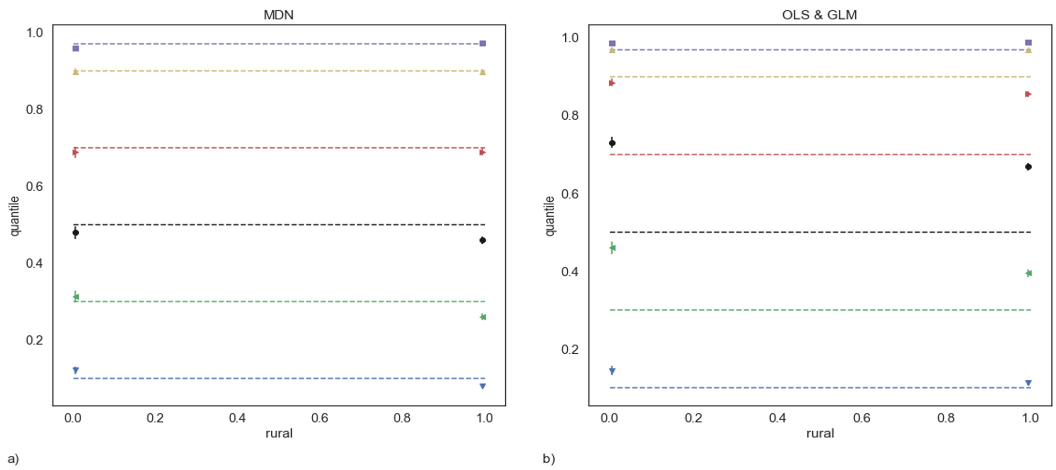

Figure 2.4: Inverse quantile profile plots for households living in rural (rural =1) or urban (rural=0) areas. These plots are generated using the test set and for the "MDN" (a) and the "OLS & GLM" model (b).

In Fig.2.4, we have two columns that correspond to the living areas of households, using 0 for those living in an urban area and 1 for those living in a rural area, and the considered quantiles are 0.1, 0.3, 0.5, 0.7, 0.9, and 0.97. This figure compares our "MDN" model to the benchmark, the "OLS & GLM" model. We can see from these inverse quantile profile plots that each quantile is predicted relatively well with the "MDN" model for the two groups of households. However, the "MDN" model shows a slight tendency to deviate from the uniform distribution for rural households, especially at the 0.3 and 0.5 quantiles. On the other hand, the "OLS & GLM" model shows a significant pattern of deviation from the uniform distribution across all quantiles for rural and urban households (see Fig.2.4).

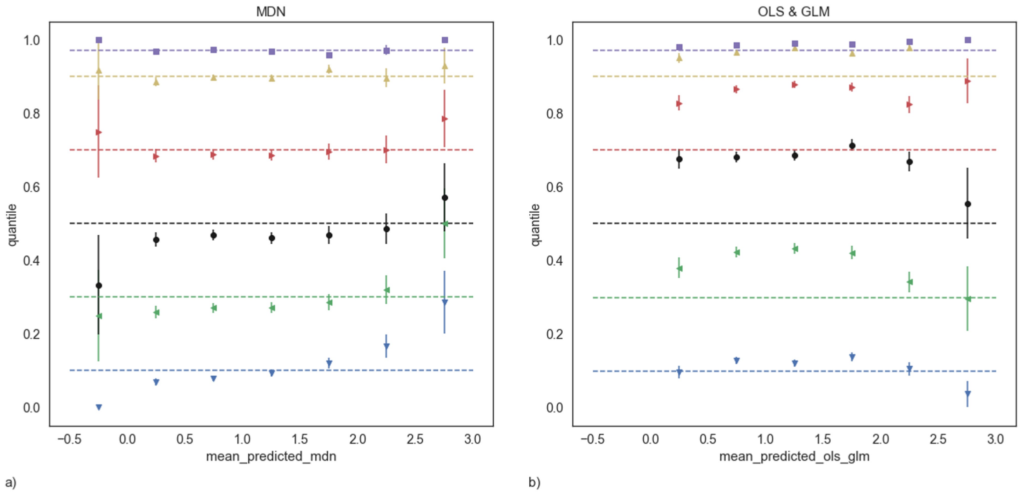

Figure 2.5: Inverse quantile profile plots for the mean of log of real total consumption expenditure predictions in the test set on the x-axis.

Fig.2.5 shows the inverse quantile profile plot using the predicted mean of the outcome variable as the graph's x-axis, subdivided into five intervals with a width of 0.5, from -0.5 to 3.

The "OLS & GLM" model shows an apparent deviation from the uniform distribution across the full range of mean prediction values and quantiles. At the same time, we can also see several deviations from the expected uniform behavior for the "MDN" model. For mean prediction of the outcome less than 0, the "MDN" model deviates significantly from the expected behavior and points toward an overprediction of the mean, especially around the 0.5 quantiles. Moreover, for a mean prediction greater than 2.5, the pattern of deviation indicates an underprediction of the mean parameter.

We also evaluate the out-of-sample prediction performance of the two models by using three different quantitative metrics. The first one, Mean Square Error (MSE), assesses the performance of the two models in predicting the mean parameters, while the Negative Log-Likelihood and the EMD accuracy (as described in sections 2.2 and 2.3.1, respectively) allow us to determine the accuracy of the predicted PDF (see Table 2.1). In table 1 presented below, the MDN model shows a relatively small improvement over the "OLS & GLM" model in predicting the mean parameter. However, it significantly improves predicting the household's well-being distribution compared to the "OLS & GLM," which is expected from the qualitative findings in figures 2.2 to 2.5.

Table 2.1: Accuracy results for the PDFs predictions

	MDN (N=3,432)	OLS & GLM (N=3,432)
MSE for mean prediction	0.21	0.23
Negative Log Likelihood	0.63	1.08
EMD accuracy	0.90	0.74

2.4.2 Evaluating the resilience score predictions

The resilience score predictions are obtained as the complement of the cumulative distribution function of the predicted PDF of well-being above the national poverty line or international poverty line. Doing so allows us to assess the effect of different poverty lines on the predicted resilience scores. Evaluating these resilience scores means assessing their correspondence with the well-being measure using statistical comparison methods. Again, the "MDN" predictions are compared to the benchmark model "OLS & GLM."

Our first comparison describes the predicted resilience scores obtained from both models, "MDN" and "OLS & GLM," firstly through their summary statistics (see Table 2.2) and then kernel density estimates of their distribution.

Table 2.2: Descriptive statistics of the predicted resilience scores

	MDN (N=3,432)				OLS & GLM (N=3,432)			
	Mean	SD	Min	Max	Mean	SD	Min	Max
RS with international poverty line	0.68	0.29	0.04	1	0.77	0.22	0.15	1
RS with national poverty line	0.52	0.32	0.01	1	0.63	0.28	0.06	1

Notes:RS=Resilience Score.

As shown in Table 2.2, on average, the predicted resilience scores from the "OLS & GLM" model are 8 points greater than those obtained from the "MDN" model when using the international poverty line and 11 points when using the national poverty line. Indeed, on average and in the test set, the "MDN" model predicted a 68 percent and 52 percent chance for a household to remain over time above the international and national poverty lines, respectively. The "OLS & GLM" model increases these percentages to 77 percent and 63 percent, respectively. This gap between the resilience score predicted from the two models has implications regarding the amount of effort needed "to build" a household's resilience. Moreover, this difference between the two models is exacerbated at the bottom of their distributions. For example, the minimum resilience score predicted by MDN with the international poverty line is 0.04, while for the "OLS & GLM" model, the predicted minimum value is 0.15. This gap at the bottom of the distributions is less exacerbated when considering the national poverty line in predicting resilience scores.

Overall, the resilience scores predicted with the national poverty line are smaller than those predicted with the international poverty line for both models, which is expected since the national poverty line is greater than the international poverty line.

Besides this difference in the two cases presented above, the KS-test (p-value below 0.01) also shows that the distribution of the predicted resilience score from the two models is statistically different, whether one considers the international poverty line or the national poverty line (see Fig.2.7).

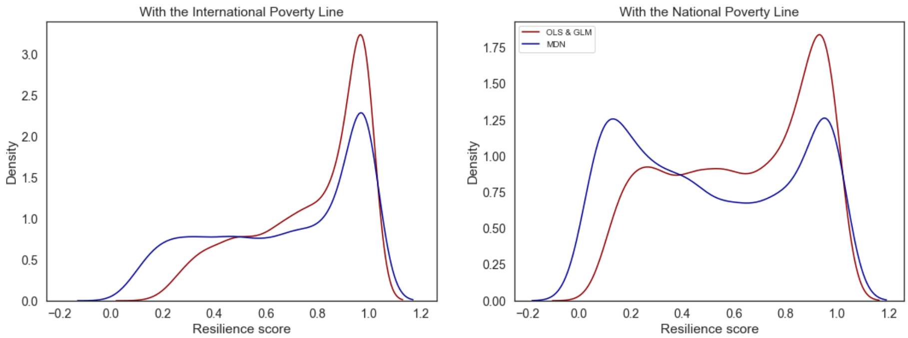

Figure 2.6: Kernel densities of the predicted resilience score from the "MDN" and "OLS & GLM" models, with international and national poverty lines.

The distribution of resilience scores predicted from the two models exhibits two picks at lower scores (i.e., between 0 and 0.4) and higher scores (i.e., between 0.8 and 1.0), a bimodality visible with the national poverty line than with the international poverty line. For the two poverty lines considered, one can see that, at lower scores, the distribution of resilience scores predicted with the "MDN" model dominate those predicted with the "OLS & GLM," while we observe the opposite at higher resilience scores. The differences in these distributions imply that the two models would generate different prevalence of resilience levels or resilience capacities within the population, leading to different descriptive statistics conclusions.

The other comparison we made aims to answer the question of whether the resilience scores predicted by these two models order households in the same way in terms of their resilience or resilience capacities. Table 3 shows Spearman, and rank-order correlation coefficients across the predicted resilience score and the outcome for the two considered poverty lines. Consistent with the findings that, at higher and lower scores, the distributions of the predicted resilience scores from the two models are similar (see Fig.2.7), we find a strong correlation coefficients between them, confirmed by Kendall's rank correlation (see Section 3 in the Appendix). The "MDN" and "OLS & GLM" models use the same variable to predict the resilience score, partially explaining the strong correlation.

Table 2.3: Spearman's rank correlation coefficients for the test set

	RS- MDN	RS- OLS & GLM	Outcome
International Poverty Line			
RS- MDN	1		
RS- OLS & GLM	0.95*	1	
Outcome	0.74*	0.75*	1
National Poverty Line			
RS- MDN	1		
RS- OLS & GLM	0.95*	1	
Outcome	0.75*	0.76*	1

Notes:* indicates statistical significance at a 1% level. RS-MDN: Resilience score predicted with MDN, RS-OLS&GLM: Resilience score predicted with OLS & GLM. Outcome: Log of total consumption expenditure per capita per day.

We also find a relatively high-rank correlation coefficient between each predicted resilience score and the outcome they intend to correspond to, even if imperfectly. Both models' two resilience scores have almost the same correlation coefficient with the outcome for the two considered poverty lines, which is expected since they directly integrate the outcome indicator in their construction.

Related to the previous results, we are also concerned about whether these two resilience scores similarly rank the least resilient households. For example, Table 2.4 shows households ranked in the bottom 20% by one measure (the rows), which are also likely to be in the bottom 20% of another measure (the columns).

Table 2.4: Resilience scores, with national poverty line, ranking- correspondence of the "Bottom 20%" – for the test set

		Also in bottom 20% of ranking by...		
		RS- MDN	RS- OLS & GLM	Outcome
In Bottom 20% of ranking by ...	RS- MDN	100%		
	RS- OLS & GLM	82%	100%	
	Outcome	59%	60%	100%

Notes: RS-MDN : Resilience score predicted with MDN, RS- OLS & GLM: Resilience score predicted with OLS & GLM. Outcome: Log of total consumption expenditure per capita per day.

We have an 82% membership match between the resilience score predicted by the "MDN" model and those predicted by the "OLS & GLM" model. Also, the percentage match of membership between each predicted resilience score with the outcome is almost the same (around 60%). These two predicted resilience scores identify the same household reliably, whether or not we focus on the bottom of the distribution.

These results, not shown here, do not change when one considers the international poverty line in predicting resilience scores.

For least resilient households, we are also concerned with knowing the amount of effort required to build their resilience. Even if both models identify the same households to prioritize in the targeting program, the "OLS & GLM" model underestimates the effort needed to build these households' resilience compared to the "MDN" model. For example, this effort can be translated in terms of the amount of cash transfer needed to build their resilience in a cash transfer program. Knowing more precisely this amount is significant since it is a key to the success of the targeting program. Because one thing is to identify the households most in need correctly, and another is to know what amount of support they will need to lift them out of their precarity durably.

In addition to the previous findings, the two predicted resilience scores might generate quite a similar population description. Because they similarly identify those with high or low levels of resilience, even if the resilience scores are, on average, overestimated with the "OLS & GLM" model compared with the "MDN" model. Therefore, the next step is to see if we will come to the same conclusions regarding the population's prevalence of high or low resilience.

To compare the prevalence of resilience in the test set between the two models, we constructed three classes of resilient status using the predicted score: the non-resilient with a score lower than 0.5, the resilient with a score between 0.5 and 0.8, and the most resilient with a score greater than 0.8.

Table 2.5: Repartition of households according to their resilience status

	MDN (N=3,432)	OLS & GLM (N=3,432)
International Poverty Line		
Non-Resilient (RS<0.5)	0.31	0.16
Resilient (0.5<=RS<=0.8)	0.24	0.29
Most Resilient (RS>0.8)	0.46	0.55
National Poverty Line		
Non-Resilient (RS<0.5)	0.51	0.35
Resilient (0.5<=RS<=0.8)	0.21	0.28
Most Resilient (RS>0.8)	0.28	0.37

Notes:RS=Resilience Score.

As shown in Table 2.5, the two models show a different picture of the prevalence of resilience across the three classes, and the two considered poverty lines. For example, when considering the international poverty line, the "MDN" model identifies 15 percent more households as non-resilient than the "OLS & GLM" model in the test set. In contrast, this model identifies fewer households as resilient (24 percent vs. 29 percent) or more resilient (46 percent vs. 55 percent) compared to the "OLS & GLM" model. We observe the same pattern when considering the national poverty line, but with a big contrast between the two models. Indeed, when considering the national poverty line, the "MDN" classifies half of the households in the test set as non-resilient, and the other half is split between resilient (21 percent) and most resilient (28 percent). On the other hand, the "OLS & GLM" classifies 35 percent of households in the test set as non-resilient, 37 percent as most resilient, and 28 percent as resilient.

Although these two models rank households in the same way according to their level of resilience, the fact remains that, in terms of prevalence and incidence of resilience or non-resilience, they give a completely different picture of the same population in the same data. Moreover, this picture may be less or more contrastive depending on whether one considers the national or the international poverty line in predicting household resilience scores.

In addition to this difference between the two models in describing the prevalence of resilience in the same population, Tables 2.6 and 2.7 show that the amount of effort required to move a household from one resilient status to another is different, depending on whether one considers the "MDN" or the "OLS & GLM" model, and the considered poverty line.

Table 2.6: The average amount of effort needed to move from one class to another-whit the International poverty line-For the test set

For MDN model			
		To…	
Move from…		Resilient* (0.5<=RS<=0.8)	Most Resilient* (RS>0.8)
	Non-Resilient (RS<0.5)	0.20 (0.12)	0.55 (0.12)
	Resilient (0.5<=RS<=0.8)	-	0.20 (0.09)
For OLS & GLM model			
		To…	
From…		Resilient (0.5<=RS<=0.8)	Most Resilient (RS>0.8)
	Non-Resilient (RS<0.5)	0.12 (0.08)	0.47 (0.08)
	Resilient (0.5<=RS<=0.8)	-	0.19 (0.09)

Notes:* the threshold used for the resilience class is 0.5, while the threshold for the most resilience is 0.85. Therefore, a household resilience score must be greater than these thresholds to enter these classes. The values presented are the average resilience gap between the corresponding threshold to enter the new class and the household resilience score. For example, for a given household to move from a non-resilient status to a resilient status, the amount of the effort is 0.5 minus its current resilience score, and to move from a resilient status to the most resilient status, the amount of the effort is 0.85 minus its current resilience score. Values in parentheses are standard deviations.

Table 2.7: The average amount of effort needed to move from one class to another-whit the National poverty line-For the test set

For MDN model			
		To…	
Move from…		Resilient* (0.5<=RS<=0.8)	Most Resilient* (RS>0.8)
	Non-Resilient (RS<0.5)	0.27 (0.14)	0.62 (0.14)
	Resilient (0.5<=RS<=0.8)	-	0.20 (0.09)
For OLS & GLM model			
		To…	
From…		Resilient (0.5<=RS<=0.8)	Most Resilient (RS>0.8)
	Non-Resilient (RS<0.5)	0.20 (0.11)	0.55 (0.11)
	Resilient (0.5<=RS<=0.8)	-	0.20 (0.09)

Notes:* the threshold used for the resilience class is 0.5, while the threshold for the most resilience is 0.85. Therefore, a household resilience score must be greater than these thresholds to enter these classes. The values presented are the average resilience gap between the corresponding threshold to enter the new class and the household resilience score. For example, for a given household to move from a non-resilient status to a resilient status, the amount of the effort is 0.5 minus its current resilience score, and to move from a resilient status to the most resilient status, the amount of the effort is 0.85 minus its current resilience score. Values in parentheses are standard deviations.

According to the "MDN" model, and considering the international poverty line, a household in the test set needs, on average, to increase its probability of remaining above the poverty line by 20 percent to move from a non-resilient status to a resilient one. In contrast, one needs 8 points less this amount of effort with the "OLS & GLM" model. The same situation is also observed when one needs to move a household from a resilient status to the most resilient one. We came to the same conclusion when considering the national poverty line. These findings have implications in policy design which aim to build household resilience, as well as in the assessment of their effectiveness. In both cases, these models may be used to construct the household resilience score, the outcome of the evaluation strategy of the policy. Using an inaccurate model to compute the resilience score may be misleading in assessing the effectiveness of the policy.

The predicted resilience scores from each of the two models are meant, by construction, to describe the current household's poverty status better and predict its future state, which led to our subsequent comparison, the out-of-sample predictive performance of the predicted resilience score. This comparison is performed in the time domain as described in section 2.4 (see Table 8).

Table 2.8: Targeting accuracy of the predicted resilience scores

	Accuracy	Precision	Recall	F1-score
International Poverty Line				
Non Resilience (RS<0.5)				
	Accuracy	Precision	Recall	F1-score
MDN	0.80	0.67	0.67	0.67
OLS & GLM	0.78	0.78	0.41	0.54
Non Resilience (RS<0.8)				
MDN	0.71	0.52	0.92	0.66
OLS & GLM	0.77	0.59	0.85	0.70
Standard approach	0.79	0.69	0.56	0.62
National Poverty Line				
Non Resilience (RS<0.5)				
	Accuracy	Precision	Recall	F1-score
MDN	0.79	0.75	0.82	0.78
OLS & GLM	0.77	0.84	0.63	0.72
Non Resilience (RS<0.8)				
MDN	0.71	0.62	0.95	0.75
OLS & GLM	0.76	0.69	0.91	0.78
Standard approach	0.77	0.79	0.68	0.73

Notes:RS=Resilience Score.

As shown in Table 2.8, the predicted resilience score outperforms the standard approach, which uses the prior household poverty status to predict its future state in all the cases (see the AUC metrics in Fig.7).

With the international poverty line, the predicted resilience status's overall targeting performance, measured with the F1-score, from the "MDN" model is greater than the one obtained from the "OLS & GLM" model in the first case (RS<0.5). In the second case (RS<0.8), the F1-score of the "MDN" model decreased slightly, while the "OLS & GLM" model improved (0.67 vs. 0.66 for the MDN model and 0.54 vs. 0.70). For both models, going from the first case to the second case is associated with a lower precision while the recall increases considerably, which results in an increase in inclusion errors and a decrease in exclusion errors. The choice of the probability threshold depends on the trade-off between inclusion and exclusion errors. Generally, in the fight against poverty, one would opt for a targeting method with low exclusion errors, which is desirable from a humanitarian perspective, where it is better to prioritize not missing the households that prove poor. At the same time, and in a context of budgetary constraints, we would also like to reduce inclusion errors to ensure that targeting policies are efficient. Therefore, the 0.5 probability threshold for identifying the household's resilience status and the "MDN" model would prevail in this context. Indeed, at this threshold, with this method, the inclusion and exclusion errors are identical and equal to 0.33, whereas, with the "OLS & GLM" method, these errors are 0.22 and 0.46, respectively. At this threshold, and with the national poverty line, the performance of the two models improves significantly with the relative dominance of the "MDN" model. This finding is promising and shows the advantage of using the "MDN" model over the "OLS & GLM" in predicting the household-specific resilience status.

To account for the choice of the probability threshold in assessing the targeting performance of the predicted resilience statuses, we construct a ROC curve (see Fig.7) to compare the performance of the two models when using the national or international poverty line. As seen in Fig.7, the performance of the two models is comparable, and both dominate the standard approach.

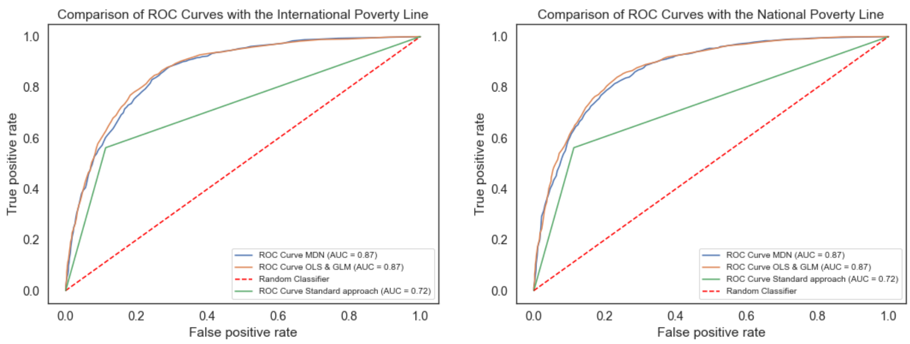

Figure 2.7: The ROC curves to assess the targeting performance of the predicted resilience status from the two models with the international and national poverty lines

Overall, the predicted resilience status with the “MDN” model shows a better out-of-sample targeting performance, in line with its much better accuracy in predicting household-specific PDF compared to the "OLS & GLM," our benchmark model.

Moreover, the proposed "MDN" approach performed slightly better than the two stages "OLS & GLM" approach in accurately predicting household-specific PDF of well-being, which are translated into its specific resilience score and status. Also, even if the results show that the predicted resilience scores from both models are comparable in how they rank households in the population, the "OLS & GLM" model seems to overestimate the chance for a given household to remain above the poverty line.

2.5 Conclusions

This paper proposes an approach that leverages ML tools to predict household-specific resilience. Our approach defines resilience as a probability of remaining above some minimal standard of living conditionally of some observable characteristics and exposure to shocks, as proposed by Barrett and Constas (2014). It also builds upon the measure of resilience based on a conditional moment approach proposed by Cissé and Barrett (2018), which serves as a benchmark.

To predict the household-specific resilience score, we propose first to predict its conditional well-being probability density function. Then the predicted resilience score can be computed as a probability of remaining above a pre-specified threshold. For this purpose, we use an approach that combines a Neural Network with a Gaussian Mixture Model to predict household-specific conditional well-being probability density function.

We test the proposed approach on household data from Nigeria and compare it to the sequence of two regressions, the benchmark. Our approach outperformed the benchmark in accurately predicting, out-of-sample, the household-specific conditional well-being probability density function (PDF). To evaluate the accuracy of the household-specific conditional well-being PDF, we employ techniques using the probability integral transform as proposed by Diebold et al. (1998).

Our approach can accurately predict a household's resilience score by correctly predicting its conditional well-being PDF.

The results show that our approach and the benchmark order similarly households in terms of their resilience from the less to high resilience score. However, the out-of-sample targeting performance of the proposed approach is better than the benchmark. Moreover, by not correctly predicting the household-specific conditional well-being PDF, the results also show that the benchmark approach tends to overestimate the household predicted resilience score, which has implications for quantifying the prevalence of resilience; and the amount of effort needed to build resilience in the same population.

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Chapter 3

How Do Agro-Pastoral Policies Affect the Dietary Intake of Agro-Pastoralists? Evidence from Niger

This chapter is joint work with Christophe Muller (AMSE).

3.1 Introduction

Agricultural policies in poor developing countries are often motivated by the improvement of the nutritional status of rural populations. Often, agricultural policies have not only the presumed effect of increasing agricultural producers' incomes, but also of enhancing dietary intakes (Carletto et al., 2015). However, this hypothesis is certainly not systematically satisfied, notably because many policies are deficient. In these conditions, the actual occurrence of these two effects is doubtful. Besides, a mismatch between income levels and nutrition indicators has been often observed in household surveys and in the literature (for example, richer households in the same village can have worse nutritional status) (Salois et al., 2012; Zhou and Yu, 2014; Ogundari and Abdulai, 2013)

Do the studied policies yield better dietary intake and higher profit, here in the case of agro-pastoralists in Niger? Are there improvements in diet because increased profit translate into better nutrition, or because of alternative channels?

For example, Ogutu et al. (2020) find in Kenya that agricultural commercialization improves dietary quality. Improving dietary intake can boost nutrition status, for example, as measured by anthropometric variables (e.g., in (Puentes E. et al., 2016)). Accordingly, household agricultural profit remains the indicator most widely used to monitor the success of agricultural policies. However, it is unclear whether the nutritional impact of these policies actually goes through the agricultural household profit and in which proportion or whether it goes through other, often overlooked, channels.

Learning that a nutrition effect does prominently operate through the agricultural profit would first corroborate a potential nutritionment of the policy mechanism targeting profit. This is far from obvious in contexts of missing and imperfect markets, in which the separation of production and consumption decisions has often been rejected (Benjamin (1992); Muller (2014)) and where household choices may therefore involve more complex and extended transformations.Moreover, it would direct the attention of policy makers toward the financial incentives that producers follow in developing and selecting their activities. In particular, changes in activity specialization or sector may occur if policies affect profits and returns discordantly for distinct activities. Furthermore, activity switches may be accompanied by fundamental transformations in the lifestyle of households, including in their dwelling and consumption habits, and in the constraints they face for gathering the ingredients of their meals. As we will show below, this may imply, in our setting that is Niger, that some policies that foster pastoralist incomes may have harmful consequences for the calorie intake of some beneficiary households.

Instead, finding that nutrition effect of an agricultural policy operates through channels other than agricultural profit or other production level measures would push policy makers to adjust their perspective on how the policy impacts nutrition. Policy makers would be pushed to turn their focus to other pathways less directly connected to market and production processes. For example, local community networks, diversion of assistance, informal exchanges and gifts, and power games within and between households may be comprised in the repercussions of the policy. All, these alternative policy channels may require more attention from policy makers.

Our goal is to investigate these issues. To do so, using statistical mediation analysis, we will assess the relative importance of direct and indirect (through profit) effects of some pastoral policies in the case of Niger. In particular, the financial incentives generated by policies for pastoral versus other activities will be highlighted. Furthermore, lifestyle switches will be emphasized for assessing agricultural policies. Finally, we will point out an overlooked perverse effect of some policies: household nutrition may be damaged by changes in diets that accompany the triggered switches in activities and lifestyles. For example, sedentary agricultural households who move to pastoral transhumance lose access to valuable cereal sources of calories. All these questions are relevant for many agricultural regions and poor developing countries. We will shed some light on them by investigating agro-pastoral households in Niger.

The linkages between agricultural and pastoral activities, diets and nutrition statuses may be complex. For semi-subsistence agricultural households, raising the level of a household's food output should generally increase its food availability and, as a result, its food intake. However, as agricultural households have generally become increasingly market oriented over the last decades, they also typically purchase a substantial share of their food on markets to meet their food needs (The World Bank, 2007; Herforth and Harris, 2014). Moreover, with access to markets and extra income from output sales, they can purchase higher quality food.

In developing contexts, diverse authors have found that a household's production strategies may influence its nutritional and health statuses beyond the effect of its varying agricultural profit.[1] Here, we examine a specific link in these potential interactions, namely, how agricultural profit may impact dietary intake. However, one issue is that the health and nutrition status of producers may also directly affect their productivity and efficiency, as found by Croppenstedt and Muller (2000) in Ethiopia. Moreover, food aid programs sometimes simultaneously provide food aid and production-related assistance (as in Brück et al. (2018)). This implies that endogeneity issues may arise when estimating an equation determining dietary intake in which agricultural outputs or profits are included as explanatory factors.

To investigate all these issues, we conduct a statistical mediation analysis of agro-pastoral policies by using methods akin to those discussed in (Heckman and Pinto, 2015; Vanderweele, 2015).Mediation analysis has already been used to analyze the impact of promotion campaigns for staple food adoption on dietary intake (De Brauw et al., 2018).Instead, we inspect household pastoral profit as a potential mediator in policies aimed at raising pastoral profits. We apply this new approach to three types of policies: (i) livestock extension services, (ii) veterinary services, and (iii) input subsidies. As mentioned before, in addition to their indirect effects through profit, these policies may have direct effects. For example, they may affect nutritional outcomes through the resale or transfer of the received goods and services to other households. Neglecting these potential mechanisms, as well as others, may bear consequences

[1] (Muller, 2009; Carletto et al., 2015; Dillon et al., 2015)

for household food consumption and dietary intake.

We will show that the mix of the selected policies and selected outcomes evinces the diversity of the effects at play. Some policies (extension services) enjoy significant (positive and negative) average treatment effect on almost all outcomes. Others (veterinary and feed) do not have significant effects on some outcomes (calories). Some outcomes (diet diversity) are improved by all policies, including through agro-pastoral profit. Other outcomes only mostly react to some specific policies, or only through the effects of these policies passing through profit.

This is this variety of patterns of effects that makes the mediation analysis attractive. Not all policy-outcome pairs have the same underlying mechanisms and channels. In particular, mediation analysis will show that some insignificant average treatment effects of policies are in fact the result of offsetting significant direct and indirect (through profit) effects. Mediation analysis, in the studied case, will also show that most selected policies have little direct effect beyond their effect through raising profit.

The rest of the paper is organized as follows. In Section 2, we present the context and the data. Section 3 discusses the empirical strategy, while Section 4 reports the estimation results. Finally, Section 5 concludes the paper.

3.2 Context and Data

3.2.1 Context

Niger is a large, landlocked African country with a population of 17 million in 2014. Forty percent of Niger's GDP is derived from the agricultural sector, with 11 percent from livestock (Ministère de l'Elevage, 2016). 87 percent of the population are involved in the livestock sector as a primary or secondary activity. On average, 10 percent of rural households' income and up to 43 percent of the income of households in pastoral zones comes from livestock. In a survey conducted in 2011 by the National Institute of Statistics in Niger on living standards and agriculture, Zezza and Issa (2012) found that 77 percent reared livestock in rural areas in 2005. These households kept, on average, 2.8 tropical livestock units (TLUs)[2] per household.

Most of the Nigerien households rearing livestock are poor. de Haan (2016) states that between 2008 and 2013, up to 30 percent of the pastoral and agro-pastoral populations were very poor, and 30 percent poor, although the asset value of livestock is omitted.

The combined effects of climate change, drought, floods and desertification, as well as demographic pressure have brought the pastoral economy into disarray. In the purely pastoral sector, mean livestock ownership is only 1.9 TLUs per capita, and 0.6 TLU per capita in the agro-pastoral sector. According to de Haan (2016), these

[2]Tropical livestock units are livestock numbers converted to a common unit. Conversion factors are: cattle = 0.7, sheep = 0.1, goats = 0.1, pigs = 0.2, chickens = 0.01.Visit Harvest Choice website for more details. The benchmark tropical livestock unit is commonly taken to be an animal of 250 kg liveweight (International Livestock Centre for Africa, 1988)

levels are low when compared to "the minimum required to meet basic needs, avoid livestock inbreeding, and recover from drought", which is between 2.5 and 4 TLU per capita for pastoralist households and half of that for agro-pastoralist households. Below this level, households are confined to poverty even in good times. In contrast, households above this threshold can not only regenerate herds after droughts, but also use their animals to maintain the social networks.

Niger is one of the most vulnerable countries in the world, with 20 percent of rural households being food insecure in any given year (Ballo and Bauer, 2013). In 2010, 26.8 percent of agro-pastoralist households were affected by food insecurity, with global acute malnutrition (GAM) among children under five years very severe in agro-pastoral and pastoral areas. In the Tilaberi region, GAM was up to 14.8 percent, near the WHO's maximum threshold of 15 percent (United State Agency for International Development, 2011). This calamity was largely a consequence of the 2009/2010 food crisis, which was characterized by harvest collapse, a very short rainfall period, and consecutive years of prolonged droughts.

This paper uses data from a specialized survey collected by the Ministry of Livestock in Niger. This survey was conducted for monitoring two projects: "PRAPS: Projet Régional d'Appui au Pastoralism au Sahel" and "PASEL: Programme d'Appui au Secteur de l'Elevage".

We can access only the first wave of this survey, which was conducted in October 2016[3]. The survey covered all the seven regions of the country, and 1,350 pastoral and agro-pastoral households were sampled. First, 90 villages were selected proportionally to their size without stratification, as recorded from the national directory of localities. Then, 15 households were randomly drawn with stratification with respect to the herd size, from each of the villages (small, medium and large herders). Some agropastoral policies could induce non-pastoral households to enter these activities. We cannot control this potential entry with these data. On the other hand, we found no indications that such process is actually taking place, either in the academic, or in the administrative literature, Niger's statistical sources, or during the interventions and focus groups that we conducted in Niger.

The surveyed households were asked about their socio-demographic characteristics, budget, food consumption, agro-pastoral production, livestock holdings, agro-pastoral sales and the prices they face individually. The same survey provides information on different shocks that the households suffered (shocks related to animal fodder, animal diseases, and access to water) and on their strategies in response to these shocks. Finally, there is precise information on the access these households had to the three examined policies for this study: input subsidies, veterinary services and livestock extension services.

In 2011, the country put in place a long-term agricultural and food policy program, denoted "Initiative 3N: les Nigériens Nourissent les Nigériens" (Nigeriens Nourishing Nigeriens), for the livestock sector with the aim to (i) increase fodder availabil-

[3] The other waves, which are not accessible officially, cover too small a subsample to be usable for our analyses.

ity by creating livestock feed warehouses, livestock feed banks, mills, and municipal supply centers; (ii) increase water availability by digging wells; (iii) develop vaccination for animals; (iv) enhance extension services targeted toward pastoral and agro-pastoral households; and (v) give fodder, multi-nutrient block and fodder seeds to vulnerable pastoralist and agro-pastoralist households. We now discuss the three initiatives of this program.

The livestock extension services enhanced by the Initiative 3N include two types of professional advice: the first is related to the use of livestock feed, while the second encourages households to use modern animal health services, appropriate breeding techniques and modern feeding. To obtain the first type of advice, households must visit a livestock feed bank, also called "the peasant house". These peasants' houses are held by government technical services, municipalities, farmers' associations or cooperatives. The livestock feed bank aims to i) bring livestock feed closer to remote households and ii) provide a "security stock" that can be mobilized during the hot and dry season when livestock feed is scarce on the market and particularly expensive. The second type of advice routinely provided at the start of the pastoral season every year, and is offered by farmers' associations and the technical services department of the Ministry of Livestock.

Private veterinary services are delivered either by an individual private veterinarian or a local private veterinary assistance. On the one hand, private veterinarians can be found at the department level. They often hold veterinary medicines with the mandate to deliver free vaccination campaigns financed by the government. Local private veterinary services are led by a private veterinarian who runs a network of about thirty auxiliaries. These auxiliaries may be community agents, such as villagers chosen by the community, who are trained and associated with the private veterinarian. Local private veterinary and their auxiliaries provide households with various animal health services, such as vaccination, treatment of animal diseases, and advice on a wide array of issues.

Every year, the government assesses the country's fodder deficit and purchases fodder to meet needs of deficit areas. This fodder is offered to peasant households at moderate prices. However, it never covers more than fifty percent of what is needed (Ministère de l'Elevage, 2015).

Furthermore, in order to generate instrumental variables addressing the issue of endogeneity of agro-pastoral profit, GPS coordinates are used for matching each surveyed household with local precipitations and temperature data as detailed in the section I of the Appendix. In this study, focus is on households that own sheep and cattle, our population of reference, as explained in the section II of the Appendix.

3.2.2 Data and summary statistics

Table 1 reports some descriptive statistics for the variables used in this paper. The average age of the household head in our sample is 45 years, and nearly 95 percent are male. The majority of the heads (94 percent) have no education, and only 4 percent received primary education. The average size of a household is 7 members, most of whom are children.

Our sample is mainly composed of households whose head belongs to the Fulani ethnic group (55 percent), followed by Tuareg (23 percent) and Haussa (14 percent). The seven regions of the country are grouped into two zones: the North and the South. The North is formed by the Agadez, Diffa, Maradi and Zinder regions and the South by the Tahoua, Dosso and Tillabery regions. Most of the households in our sample (60 percent) are in the South.

As previously stated, households were classified into three categories according to the size of their herds: small herders (5 sheep and 4 cattle, on average), medium herders (10 sheep and 8 cattle) and large herders (29 sheep and 14 cattle). The majority (56 percent) of households in our sample are in the small herders category. Only 15 percent of households surveyed are large herders. For all categories combines, the average number of animals per household is ten for sheep and seven for cattle.

Table 3.1: Summary statistics

Variables	N. Obs	Mean	Std. Dev	Min	P25	P50	P75	Max
Sociodemographic variables								
Sex of household head (1 if male)	600	0.95	0.23	0	-	-	-	1
Age of household head	596	44.76	14.66	17	33	42	55	92
Education level of household head								
- None (1 if yes and 0 otherwise)	600	0.94	0.23	0	-	-	-	1
- Primary (1 if yes and 0 otherwise)	600	0.04	0.19	0	-	-	-	1
Household size	600	7.14	3.68	1	4	7	9	25
Number of children (0-3 years old)	600	0.82	0.97	0	0	2	1	6
Number of children (4-10 years old)	600	2.02	1.66	0	1	2	3	9
Number of youths (11-16 years old)	600	0.88	1.08	0	0	1	1	8
Number of young adults (17-20 years old)	600	0.80	0.93	0	0	1	1	5
Number of adults (20 years old)	600	2.65	1.52	0	2	2	3	11
Area of residence (1 if in the South)	600	0.60	0.49	0	-	-	-	1
Ethnic group								
- Tuareg (1 if yes and 0 otherwise)	600	0.23	0.42	0	-	-	-	1
- Haussa (1 if yes and 0 otherwise)	600	0.14	0.35	0	-	-	-	1
- Fulani (1 if yes and 0 otherwise)	600	0.55	0.49	0	-	-	-	1
Livestock holding								
Number of sheep	600	10.04	31.44	0	1	4	10	130
Number of cattle	600	6.55	9.36	0	0	3	8	64
Livestock holding category								
Small producer	600	0.56	0.5	0	-	-	-	1
Large producer	600	0.15	0.36	0	-	-	-	1
Outcomes variables								
Calorie intake per capita per day (kcal)	600	3,987	3,874	16.70	1,585	2,775	4,921	21,166
Calorie intake per capita per day from cereals (kcal)	600	3,242	3,222	15.66	1,214	2,192	3,825	20,984
Calorie intake per capita per day from animal food product (kcal)	600	208.81	980	0	5.11	41.08	102	12,539
Household dietary diversity score	600	5.39	1.73	1	4	5.5	7	9
Annual profit from livestock production (Millions of CFA)	600	3.89	18.3	-1.63	0	0.21	1.15	257
Policies								
Access to livestock extension services (1 if yes and 0 otherwise)	600	0.19	0.39	0	-	-	-	1
Access to private veterinary services (1 if yes and 0 otherwise)	600	0.20	0.40	0	-	-	-	1
Access to low-cost livestock feed (1 if yes and 0 otherwise)	600	0.15	0.35	0	-	-	-	1

Notes: To calculate the calorie intake from cereals and animal food products, the considered cereals are millet, sorghum, bread, maize, and edible pasta, while the animal food products considered are meat, poultry, fish, fresh milk, curdled milk, and cheese.

The household dietary diversity score varies between 1 and 9, with an average of 5. This means that, on average, the surveyed households consume five different food groups during the year. Over this year, food consumption provided an average of 3,987 kcal per person per day for each household. However, 25 percent of surveyed households have a calorie energy intake of less than 1,584 kcal per person per day, while for 50 percent of the households, the intake is less than 2,775 kcal per person per day. Measurement issues and outliers are examined in the section III of the

Appendix.

Table 1 shows that the profit level varies greatly across households. On average, annual profit is 3.89 million CFA francs, mainly driven by high profit level of medium and large herders. Over the survey period, 25 percent of households had a zero profit, while half of households made a profit of more than 214,073 CFA francs. The households with zero profit correspond to those with very limited pastoral activity. The maximum profit loss observed is nearly 1.6 million CFA francs. This may partly be due to measurement errors and partly due to the fact that annual profit is an imperfect measure of economic activity for livestock rearing, where the production horizon may span many years.

The constructions of the outcome variables – the household dietary diversity score, the household caloric intake per capita and the household profit from livestock – are presented in the section IV of the Appendix. Then, they are each transformed into a logarithmic form for the econometric analysis. When transforming the annual livestock profit into logs, we add a constant amount to the profit level to accommodate negative values. The transformed profits are therefore log (profit + constant), where the constant is equal to the minimum observed value of profit in absolute terms, plus one.

In the sample, 20 percent of the surveyed households have access to private veterinary services, while only 19 percent and 15 percent, respectively, state that they have access to extension services and low-cost livestock feed (see section V of the Appendix for more details).

3.3 Empirical Strategy

As stated above, our aim is to investigate empirically the mechanisms behind the impact of agricultural policies on household dietary intake. Specifically, we want to assess the role of pastoral profits in this process. By contrast, mainstream policy evaluation methods primarily focus on the average treatment effect rather than the underlying causal channels that drive this effect.

In the statistical literature, analyzing the causal channel through which a policy effect occurs, with a specific interest in the role of a particular variable, is referred to as causal mediation analysis[4]. The particular variable is called the *mediator,* and in our case, it is the profit from livestock activity. Mediators in agricultural production technology have been identified by Heckman and Pinto (2015) using treatment effect estimators. Our approach mixing ATE estimators and regression estimators is somewhat akin to their econometric setting (p. 4, or eq. 19 p. 16). Consistent with this setting, the identification relies on ignorability conditions, controls, and instrument exclusion conditions.

Mediation analysis has been widely used in the social science especially in medicine, psychology and political science, in both experimental and observational studies.

[4] Imai et al. (2011); Vanderweele (2015)

There is growing interest in extending the use of this method to economics[5]. Our empirical strategy is a form of causal mediation analysis, in which we investigate the extent to which the impact of agricultural policies on pastoralist households' dietary intake in Niger is mediated by the profit from livestock activities.

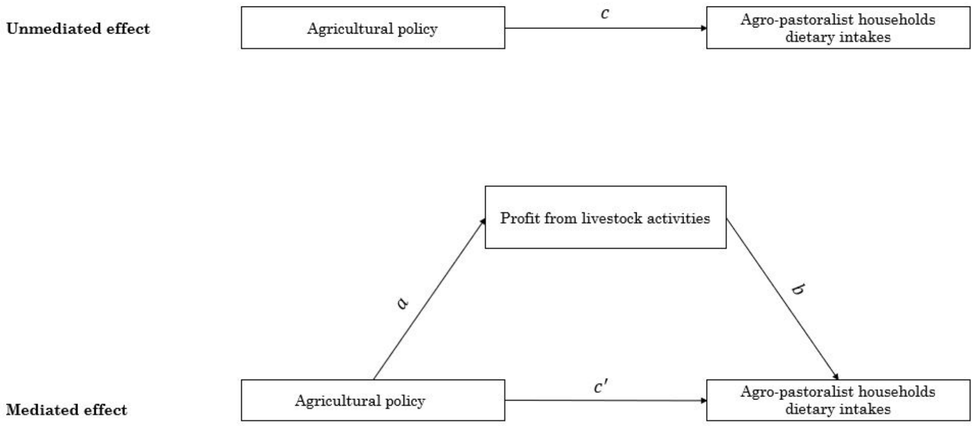

Figure 3.1: Representation of our empirical strategy

This strategy can be spelled out in terms of the four links (a, b, c and c') that are given in Figure 1. The first link represents the total effect (c in Figure 1) of the selected agricultural policies on the dietary intakes of agro-pastoralist households. Link a represents the effect of the selected policies on profit, which is the mediator, while link b represents the effect of profits on the households' dietary intake. Links a and b are used to assess the indirect effect of the policies on the households' dietary intake, that is, the effect that is channeled by profit. Finally, the last link c' represents the direct effect of the policies on the households' dietary intake, that is, the effect through channels other than annual profit.

3.3.1 Estimating unmediated effect (link c) of policies

In this step, we estimate a model of selection on observables based on the potential outcomes, with and without treatment (i.e. policy access). In Niger, households may choose to access or not to the different agricultural policies. In other words, they self-select. In this context, the identification strategy of the treatment effect relies on assuming the conditional mean independence between the treatment and the outcomes. It is therefore implicitly assumed that all the important characteristics that affect both household participation and the outcomes are observables. Given the limited data at our disposal, attempting to address identification by relying on an approximate hypothesis of selection based on observables seems to be better than neglecting selection and endogeneity issues. The separation of the effects of the different policies is discussed in the section VI of the Appendix.

To construct a counterfactual, we use the inverse probability weighted regression adjustment (IPWRA) method, discussed in Wooldridge (2010), which combines regression adjustment (RA) and inverse probability weighting (IPW). One model is

[5] Heckman et al. (2013); Kosec et al. (2018); De Brauw et al. (2018)

specified for the outcome

$$Y_i = f\left(X_i, \beta\right) + \varepsilon_i \quad , \tag{3.1}$$

and another for the treatment

$$\Pr\left(T_i = 1\right) = g(X_i, \lambda), \tag{3.2}$$

for households i = 1...N, in our sample. In equations (3.1) and (3.2), X_i is a set of covariates that influence both the outcome, Y, and the dummy variable for treatment, T. β and λ are parameter vectors to estimate, while ε_i is an error term. Function f is specified as a linear function since the outcome is continuous. As is common, we specify function g to be a probit function. Under the usual ignorability assumption, the IPWRA method delivers a consistent estimator of the effect of the treatment, even if either of the two models is miss-specified (Wooldridge, 2007).

We choose covariates that vary only a little over time to account for the fact that the data was collected five years after the beginning of the implementation of Initiative 3N. These stable covariates are surrogates for missing pretreatment covariates not affected by the treatment. Indeed, we lack baseline information on households before the Initiative 3N implementation.

The observed characteristics that are assumed to affect the outcomes and households' participation are: sex, highest reached education level and age of the household head, dwelling location (North or South), proportion of children under three, the proportion of children between 4 and 10 years old, and proportions of youths (11-16 years old) and young adults (17-20 years old). These characteristics can affect household food demand and diet composition. For example, households with children may consume more milk, even though babies rather drink mother's milk. Additionally, some households' characteristics, such as sex of the household head, its age or level of education, can affect its access to a given policy. Indeed, educated households may more easily obtain information about a policy, or may be better to implement the provided advice. Finally, although this is not well recorded, these policies may target specific households on the basis of these sociodemographic characteristics.

We include the households' ethnic group and livestock holding category to which it belongs in the treatment models since these characteristics may drive a household's willingness to access a policy, or be considered by public officials when targeting interventions. This may help us to control for potential correlations between nutritional statuses and pro-poor policies. Recall that the livestock holding categories correspond to a period prior to the survey and policy. However, we do not use these categories as a covariate of profit or outcomes because this stratification may be endogenous.

For the IPWRA method, the treatment effect is obtained by first estimating the parameters of the treatment model to generate the predicted probability to be treated for each individual, $g(X_i, \hat{\lambda})$, where$\hat{\lambda}$ is the estimate of λ. The obtained inverse probabilities are used as weights in the regressions of the outcome models for each treatment (0 and 1), so as to obtain, for each individual predicted outcome that are specific to each treatment level.

To estimate the parameters for a linear regression model for the outcome, the IPW linear least-squares regression is used for each treatment:

$$\min_{\beta_0} \sum_{i}^{N} \frac{\left[Y_i - f(X_i, \beta_0)\right]^2}{1 - g(X_i, \hat{\lambda})} \quad if \;\; T_i = 0, \tag{3.3}$$

and

$$\min_{\beta_1} \sum_{i}^{N} \frac{\left[Y_i - f(X_i, \beta_1)\right]^2}{g(X_i, \hat{\lambda})} \quad if \;\; T_i = 1 \tag{3.4}$$

Finally, the average treatment effect (ATE) is obtained by computing the difference between the means of the predicted outcomes of the two treatment groups:

$$ATE = \frac{1}{N} \sum_{i}^{N} [f(X_i, \hat{\beta}_1) - f(X_i, \hat{\beta}_0)], \tag{3.5}$$

where $\hat{\beta}_1$ and $\hat{\beta}_0$ are respectively the IPW estimated parameters of the outcome model for $T_i = 1$ and $T_i = 0$. This approach can also be used to estimate the impact of the selected agricultural policies on the presumed mediator, i.e. annual profit from livestock activities, by substituting it as the outcome variable.

3.3.2 Effect of pastoral profit

Let us now discuss the estimation method for the impact of the mediator on household dietary intake, which corresponds to the link b in Figure 1. We use a regression setting to estimate this mean effect, with control variables (X_i in the model below), which are the same as for treatment equations, except that livestock holding categories are excluded to avoid endogeneity issues.

However, as mentioned above, feedback may occur between households' production strategies and their nutritional status, and other types of confounders may arise. To control for this, we run a 2SLS regression to estimate the effect of annual profit on dietary intake. The three instruments for profit are, first, a dummy variable that characterizes the overall quality of the pastoral season as experienced by the household, second, the average annual temperature at the departmental level and third, its squared value. The first instrument reflects the way in which the household experienced the previous pastoral season in terms of water and grazing availability and livestock disease. It takes the value 1 if the household assesses the context of the previous pastoral season as favorable and 0 otherwise. With regard to the two temperature-based instruments, heat stress has been found to affect livestock health through oxidative stress, metabolic disruptions, and reduced immunity to infections (Laceteva, 2019). The temperature data at the departmental level allows us to control for the pastoral mobility of households in search of water and pasture for their animals.

Formally, this amounts to jointly estimating the following two equations for each policy j:

$$\begin{aligned} Log(Profit)_i &= \alpha_0 + T_{ij}\alpha_1 + Z'_i\alpha_2 + X'_i\alpha_3 + \omega_i, \\ Y_i &= \beta_0 + Log(Profit)_i\beta_1 + T_{ij}\beta_2 + X'_i\beta_3 + \epsilon_i \end{aligned} \tag{3.6}$$

The β's and the α's are the model vectors of parameters to be estimated, while ω_i and ϵ_i are error terms. T_{ij} is the j^{th} policy's treatment dummy for the i^{th} household, Y_i is here the outcome of interest, X_i are control variables, while Z_i denotes the three instruments for this household. While not indicated to avoid notation clutter, the parameters and error terms vary with the considered policy.

System (3.6) can be seen as specific to our mediation approach, as it allows us to estimate the impact of the mediator on the households' dietary intake while controlling for the households' access to a policy. The joint presence of the profit and policy variables in the outcome equation corresponds to the partial contributions of the direct and indirect effects to a change in outcome. The other controls are the same to those used for the ATE estimates for the policies, expect the livestock holding categories.

The three instruments are significantly linearly correlated to the logarithm of the households' pastoral profit (correlation coefficients of 0.18 for quality of pastoral season, -0.15 for the maximum local temperature in level and 0.15 for the maximum local temperature squared). They must also be uncorrelated with the error terms in the calorie intake and the dietary diversity score equations. Under this exclusion restriction, the instruments influence the outcome only through their correlations with the logarithm of pastoral profit.

The exclusion restriction for the quality of the pastoral season is justified by the fact that it is typically unexpected by households. A very bad pastoral season is characterized by a lack of water and pastureland and several spells of livestock disease outbreaks, which reduce herd fertility and milk production and negatively affect household pastoral profits. It seems reasonable to assume that, given all the controls, the quality of the former pastoral season has no direct impact on diets or that this impact can be neglected.

Regarding the other two instruments, i.e., the local maximum temperature and its squared value, the exclusion restriction is made plausible by climatic shocks being beyond the control of households and unanticipated. Then, one does not expect diet habits, given all controls, to be significantly affected by temperature. The frequency and severity of hydrological and agricultural droughts increase as the temperature rises (Vicente-Serrano et al., 2014; Amrit et al., 2018). Thus, high temperature is correlated with lower availability of pastureland and water for animals, which in turn negatively impacts milk production and animal weights and reduces the market value of animals.

Although exclusion restrictions are ultimately untestable, the observed correlations in the data are encouraging (not shown). First, the absolute value of the correlation coefficients of each instrument with each outcome is found to be approximately two times smaller than the corresponding value for the same instrument with log profit. This is consistent with the instrument mostly affecting the outcome through its correlation with profit. Second, under exogeneity of profit, the semipartial correlation of an instrument included in the outcome equation would indicate the presence of its linear correlation with the error term. Although this is no longer a consistent criterion for selecting instruments when the profit is endogenous, it is reassuring to find that the semipartial correlations of temperature in level and its squared value are not significantly different from zero for the log of total calories or the log of calories from animals.

A last point that remains to be discussed further is related to the presence of the treatment dummy in the second equation in System 6. This specification corresponds to our motivation of investigating mediation effects, and in particular indirect effects, by estimating how the treatment affects the outcome in the presence of a control by the profit variable in the same equation. In that case, consistent with the usual 2SLS formula, the treatment dummy must also be included in the first-stage equation. That is, in this context, the treatment variable is considered to be akin to an exogenous regressor. This is possible here because the controls that were introduced for justifying ignorability in the average treatment effect estimation are also introduced in the two stages of the 2SLS. They can be seen here as proxying the relevant control function, as advocated by Wooldridge (2010).

3.3.3 Estimating the indirect and direct effects

As mentioned, the indirect effect is the effect that is channeled through the pastoral profit, while the direct effect (represented by link *c'* in Figure 1) is the effect that passes through channels other than pastoral profit. The sum of these two effects forms the total effect (represented by link *c* in Figure 1).

The indirect effect is calculated as the product of the effect of policies on the mediator and the effect of the mediator on household dietary intake (links *a* and *b*, respectively, in Figure 1). The first effect *a* is estimated, on average, from the ATE formula in Equation (3.5), while the second effect *b* is obtained from the estimates of parameter β_1 in System (3.6). The direct effect *(c')* is therefore measured as the effect of the policies on the outcome when the effect of the mediator is controlled for. It is measured by parameter β_2 in the second equation in System (3.6). This parameter is identified as important household characteristics, X_i, are controlled for, to ensure the conditional independence of the treatment and outcomes.

The confidence intervals of the estimated indirect effect are computed with Monte Carlo simulations, as proposed by MacKinnon et al. (2004)[6].

[6] Starting with two estimates for the effects a and b and their standard errors, simulated random normal variables for a and b are generated to create a distribution of a*b values. With these values, confidence intervals and p-values can be estimated from their simulated analogs.

3.4 Results

3.4.1 Total effects of the policies on dietary intake

The estimates of the unmediated, or total, effect of each of the three policies on dietary intake are reported in Table 3.2. The hypothesis that the distribution of covariates is the same for the control group and the treatment group is not rejected, for each of the three policies. These distributions and tests results are shown in the section VIII of the Appendix, along with the overlapping distribution graphs of the propensity scores for the control and treatment groups, for each policy. This comfort us that it has been possible to construct two comparable groups on the basis of the covariates used in the estimations, after IPWRA weighting. This also suggests that at least one of the treatment or the outcome model is well specified. The conditional independence assumption is not rejected at the 5 percent level.

For the dietary diversity score, the average treatment effect of each of the three policies is significantly positive. Households with access to extension services saw their dietary diversity score increase by 14.3 percent relative to those who did not. Moreover, having access to private veterinary services increases the households' dietary diversity score by an almost identical extent of 14.5 percent. Finally, the total average effect of deliveries of low-cost livestock feed raises dietary diversity by 21.7 percent.

With regard to daily calorie intake per capita, only extension services have a significant impact. They decrease daily calorie intake per capita by 28 percent for households that access them. The other two policies do not have significant effects on total calorie intake. The effects of each policy are similar when considering calorie intake only from cereals. This suggests that the surprising negative impacts of extension services on the total calorie intake could be explained by a decline in the consumption of cereals.

Table 3.2: Total effect of selected policies on households' dietary intake

	Log of household dietary diversity score	Log of total daily per capita calorie intake	Log of daily per capita calorie intake from cereals	Log of daily per capita calorie intake from animals
	ATE	ATE	ATE	ATE
Extension services				
Access to extension services	0.143*** (0.03)	-0.281** (0.13)	-0.327*** (0.14)	0.261 (0.19)
Testing covariates balance: (Chi-2 tests: p-values)	[0.80]	[0.80]	[0.80]	[0.75]
Veterinary services				
Access to veterinary services	0.145*** (0.04)	-0.194 (0.15)	-0.250 (0.16)	0.066 (0.21)
Testing covariates balance (Chi-2 tests: p-values)	[0.38]	[0.38]	[0.38]	[0.47]
Input subsidies				
Access to low-cost livestock feed	0.217*** (0.03)	0.099 (0.11)	0.081 (0.12)	0.379* (0.22)
Testing covariates balance: (Chi-2 tests: p-values)	[0.93]	[0.93]	[0.93]	[0.96]
Number of Observations	596	596	596	511

Notes: ATE: Average treatment effect. Values in brackets are p-values, and values in parentheses are robust standard errors. *, ** and *** indicate significance at the 10%, 5% and 1% probability levels, respectively.

However, opposite policy effects are observed for the calorie intake from animal food products. For both extension services and the low-cost feed programs, the results show positive effects, although only the effect of the latter program is significant, at the 10 percent level. Nevertheless, a positive and small nonsignificant impact is observed for private veterinary services. The positive effects, even if not significant, of extension services and the low-cost feed programs are consistent with their presumed beneficial contribution to the dietary diversity score. Increasing the dietary diversity for households who have diets mainly composed of cereals generally implies augmenting their consumption of food products from animals. Nevertheless, the negative impact of extension services on total calorie intake raises the question of its origin. A causal mediation analysis will shed more light on this.

Three hypotheses could explain this intriguing result. The first is the presence of a perverse effect of the examined policy, which may foster households' specializing in pastoral activities at the expense of agricultural production. The second hypothesis is related to changing food habits of agro-pastoralist households, which may have substituted additional consumption of food products from animals for cereals. The third is related to measurement errors in calorie intakes. Examining these hypotheses, especially the first, is one of the aims of the next sub-sections.

3.4.2 Effects of policies on profit and production levels

Table 3.3 reports the estimated average treatment effects of the selected policies on households' pastoral profit, and their cereal and milk production levels, all in logarithms.

Table 3.3: Effects of selected policies on household profit and production levels

	Log of annual profit from livestock activities	Log of annual quantity of milk production	Log of annual quantity of agricultural production
	ATE	ATE	ATE
Extension services			
Access to extension services	0.231**	0.569***	.155
	(0.10)	(0.20)	(.16)
Testing covariates balance (Chi-2 test: p-values)	[0.81]	[0.41]	[0.79]
Veterinary services			
Access to veterinary services	0.082	0.296	0.445**
	(0.09)	(0.21)	(0.20)
Testing covariates balance (Chi-2 test: p-values)	[0.33]	[0.60]	[0.63]
Input subsidies			
Access to low-cost livestock feed	0.168	0.144	-0.167
	(0.11)	(0.21)	(0.18)
Testing covariates balance (Chi-2 test: p-values)	[0.91]	[0.96]	[0.96]
Number of Observations	595	326	482

Notes: We consider only the three mains agricultural products: millet, sorghum and cowpea. ATE: Average treatment effect. Values in brackets are p-values, and values in parentheses are robust standard errors. *, ** and *** indicate significance at the 10%, 5% and 1% probability levels, respectively.

Only veterinary services, have a significant impact on the production levels of the three mains agricultural product (millet, sorghum and cowpea)[7]. Only extension services have a significant and positive effect on the annual profit of households from livestock activities. Access to this policy increases households' annual pastoral profit by 23 percent, on average. The effects of the other two policies on profits are positive but not significant. Additionally, these two policies do not have any significant effects on milk production.

Among the considered policies, only extension services seem to have enhanced pastoral profit, especially because they are the only ones with a positive and significant impact on milk production. In contrast, veterinary services and livestock feed programs have failed to reach this objective. It is therefore interesting to learn whether the positive effect of extension services on household profits is transmitted to dietary intake.

The non-significant effect of veterinary services on household pastoral profit could be explained by households using this policy to limit the damage that diseases can cause to their herds. They do not seem to be taking a preventive approach when they decide to use this service but rather aim to care for sick animals. Therefore, when massive disease outbreaks do not occur in the considered year, the effects of this policy may not emerge. Moreover, when they face such negative shocks frequently and repeatedly, pastoral and agro-pastoral households may convert to full-time agriculture to meet their food needs in these difficult times. Indeed, there are reports about Tuareg herders in Niger switching to agriculture after experiencing livestock losses due to drought and disease (Le Point, 2019). This could partly explain the positive and significant effect of veterinary services on households' production of cereals.

Extension services, the only policy that significantly and positively affects pastoral profit and milk production, also have a negative effect on calorie intake from cereals and a positive effect on calorie intake from animals, as shown above in Table 3. Therefore, production and consumption substitution between cereals and food products from animals may have taken place after this policy, which would help to explain these effects.

[7] Of the surveyed households, 85 percent produce at least one of the three agricultural products.

3.4.3 Effects of profits on dietary intake

As discussed, these effects are estimated by running linear 2SLS regressions, in which the dietary intake measures are the dependent variables, and annual profit is an independent endogenous variable. The control variables X_i are the same as those used when modeling the total treatment effect on the outcome variables. The estimates of the mediation model are presented only for the extension services, since it is the only policy which have an effect on profit (see Table 3.4). The mediation models for the other policies are presented in the Appendix.

As explained above, to assess the direct effect of each policy, the treatment variable must be included in the second stage of the 2SLS regression. This entails the inclusion of the treatment variable in the first stage, as well, consistently with the correct formula for the 2SLS estimator. Using the included controls in the 2SLS estimation makes not only the conditional independence of the treatment and the outcome, but also the conditional independence of the instruments and the outcome more plausible.

For the extension services, the hypothesis of exogeneity of the logarithm of profit is rejected at the five percent level and under, for all the considered dietary outcomes, except for the logarithm of calories from animals. This led us to estimate the model using a 2SLS regression for dietary diversity score, total calories intake and calories intake from cereals, and an OLS regression for calorie intake from animals. The results of the overidentification tests indicate that the three instruments are valid at the five percent level. However, the results of the test of weak instruments of Olea and Pflueger (2013) suggest that our instruments may be weak. This leads us to implement the two-step weak IV methodology developed by Sun (2018), based on Andrews (2018), to compute identification-robust confidence sets.

The results of the first-stage estimation, reported in Panel B of Table 3.4, show that households reporting a favorable pastoral season have a higher observed annual profit. For these households, the availability of good pastureland and water for their herds promoted production and profit. The coefficients of the two temperature instruments are also highly significant.

The coefficient of extension services in this equation is significant and similar to that obtained when estimating the effect of extension services on profits with IPWRA (+22 percent with the 2SLS model and +23 percent with IPWRA), which is comforting.

Table 3.4: Mediation model for extension services

	Panel A: 2SLS/OLS			
	Outcomes			
	Log of household dietary diversity score	**Log of total daily per capita calorie intake**	**Log of daily per capita calorie intake from cereals**	**Log of daily per capita calorie intake from animals (OLS)**
Mediator				
Log of annual profit from livestock activity	0.426*** (.120) [0.279, 0.821]	-0.712** (.236) [-1.562, 0.368]	-0.940*** (.267) [-1.995, 0.605]	0.412*** (.111)
Policy				
Access to extension services	0.03 (.057)	-0.085 (.183)	-0.08 (.202)	0.141 (.206)
	Panel B: First Stage			
	Mediator			
	Log of annual profit	**Log of annual profit**	**Log of annual profit**	**Log of annual profit**
Policy				
Access to extension services	0.22** (.106)			
Instruments				
Pastoral season (1 if good)	0.303*** (.103)			-
Annual maximal temperature in level	-21.635*** (6.471)			-
Annual maximal temperature squared	0.306*** (.09)			-
Control variables	X	X	X	X
Test of exogeneity of log profit (Robust F: p-values)	[0.00]	[0.00]	[0.00]	[0.95]
Test of overidentifying restriction (Chi 2 test: p-values)	[0.14]	[0.14]	[0.12]	-
F-Statistics for first-stage statistics for excluded instruments	8.61	8.61	8.61	-
Robust weak instruments statistic, MP test [Critical value at 10 probability level]	13.17 [14.45]	13.17 [14.45]	13.17 [14.45]	-
R Square	-	-	-	0.12
Number of observations	595	595	595	516

Notes: Values in brackets are critical p-values, and values in parentheses are robust standard errors. *, ** and *** indicate significant differences at the 10%, 5% and 1% levels, respectively. The robust test for weak instruments is proposed by Olea and Pflueger (2013) and computed using a Stata package made available by Pflueger and Wang (2015). MP: Olea Montiel and Pflueger. The confidence interval in brackets is the identification-robust LC_2sls 95 percent confidence interval for linear IV. These confidence intervals are computed using the package twostepweakiv proposed by Sun (2018). The distortion cutoff level obtained from this test is 14%, 9% and 10% for the model of dietary diversity score, total calories intake and calories intake from cereals, respectively, which does not exclude the possibility of a weak instrument The distortion cutoff level obtained from this test is 14%, 9% and 10% for the model of dietary diversity score, total calories intake and calories intake from cereals, respectively, which does not exclude the possibility of a weak instrument.

From the second equation of interest, the effect of a ten-percent increase in pastoral profit on households' dietary diversity is statistically significant and almost the same for the three policy-specific mediation models, ranging from 4.2 to 4.3 percent (see Section IX in the Appendix), which is substantial. This impact is therefore robust to the inclusion of any of the three policy dummies.

In contrast, a ten-percent increase in profit diminishes total daily per capita calorie intake by -7.5 to -7.1 percent, depending on the implemented policy. However, the significant effect of profit differs in sign depending on the whether it is assessed on calories from cereals or calories from animals. Increasing households' pastoral profit by 10 percent amounts to increasing its calorie intake from animals by 4.1 percent and lowering its calorie intake from cereals by 9.5 percent, on average. These results are in line with policies altering the dietary habits of agro-pastoralist households toward more diversified diets, with higher calorie intakes from animal products. This transition may be driven by new incentives associated with increasing pastoral profit and greater specialization in pastoral activities. In Niger, specializing in livestock activities can be accompanied by a significant change in households' lifestyle. With problems such as chronic lack of pasture and shortage of water due to frequent periods of drought, these households may turn to pastoral transhumance in search of fresh pasture. This switch in livelihood can induce households to consume easy-to-find calories from animal products, as opposed to cereals that may be hard to come by. Nomadic households may also lose access to markets for specific food products, thereby restricting their food diversity. This contrast in consumption pattern between nomadic and sedentary pastoralist or agro-pastoralist households was studied in Northern Kenya by Fratkin and Roth (2006). According to these authors, a nomadic pastoral diet is characterized by calorie-poor and protein-rich food, which is consistent with our findings.

Moreover, whether for pastoral or agro-pastoral households, those who engaged in pastoral mobility[8] the year before the survey differ from the others in terms of their mean dietary intake (see Table 8 in Section V of the Appendix). Those who engaged in pastoral mobility consume fewer calories, notably fewer from cereals, while they consume more calories from animals and enjoy higher dietary diversity than those who were not mobile. This supports our interpretation linking pastoral mobility and diet composition. In this case, a nutritionally harmful specialization of households in pastoral activities may contribute to explaining the negative impact of some agro-pastoral policies on total calorie intake.

Law et al. (2020) provide additional evidence of the declining importance of cereals in household diet, this time for Indian households. In this case, while the shift away from traditional staples is attributed to a change in food preferences, it also corresponds, as in our case, to cereals being a substitute for rather than a complement to animal products in diet.

Among the three policies, the only one with a direct effect on the dietary diversity, significant at the five percent level, is that providing livestock feed. The direct effects (that is: the effects that do not pass through profit) of each of the three policies on calorie intake, either from cereals or animals, are not significant at the five percent level. These results provide an indication of the importance of the indirect effects (i.e. the effects that pass through profit) in these data and for these policies. Thus, at first glance, designing agro-pastoral policies so that they can raise pastoral profit may seem to be a good idea, supported by the significant indirect effects associated with this mediator. Unfortunately, the direction of these indirect effects on dietary intake is probably not the one intended, with perverse negative consequences for total calories in particular. Moreover, this shortcoming is not offset by the direct effects, which are generally not significant.

[8]Pastoral mobility refers to the movement of one or more household members with animals in search of pasture and water. It is a movement of people and animals, from dry areas to wet areas with abundant grazing and water for animals.

3.4.4 Direct and indirect effects of selected policies on dietary intake

The estimated total, direct and indirect effects of the considered policies on dietary intake are recapitulated in Table 5. Livestock extension services represent the only policy with a significant impact on profits from livestock activities, and therefore, this is the only policy for which the decomposition of the total effect is relevant. All the indirect effects of the extension services are significant, at the 5 percent level, for the four dietary intake indicators. The size of these effects varies across the four outcomes. The estimates show that 69 percent of the effect of the extension services on households' dietary diversity score passes through the profit. Additionally, 66 percent of the surprising negative effect of livestock extension services on households' calorie intake from cereals is explained by the annual profit, while the direct effect on this outcome is not significant.

Table 3.5: Decomposition of the total effect of extension services on dietary intake

	Extension services			
	TE	IE	DE	IE/TE
Outcomes				
Log of household dietary diversity score	0.143*** (0.03)	0.099** (0.05)	0.03 (.06)	0.69
Log of total daily per capita calorie intake	-0.281** (0.13))	-0.164** (.09)	-0.085 (.18)	0.58
Log of daily per capita calorie intake from cereals	-0.327*** (0.14)	-0.217** (0.11)	-0.08 (.20)	0.66
Log of daily per capita calorie intake from animal food products	0.261 (0.19)	0.096** (.05)	0.141 (.21)	-

Notes:TE= Total average treatment effect, IE= Indirect average treatment effect through the annual livestock profit and DE= Direct average treatment effect. DE represents the part of the total effect that does not operate through the annual livestock profit, which is obtained in the mediation model. The values in parentheses are standard errors. The standard errors for IE are computed using simulations. This test is similar to the delta method. *, ** and *** indicate significant differences at the 10%, 5% and 1% levels, respectively.

Through a positive effect on profit, extension services increase dietary diversity score by almost 10 percent. Moreover, again through profit, extension services decrease calorie intake from cereals by 21.7 percent, while they raise calorie intake from animals by 9.6 percent. This amounts to a decrease in total calorie intake by 16.4 percent, which represents 58 percent of their total effect this outcome.

The pastoral profit therefore not only appears to be a substantial mediator of the effect of the extension services on pastoralist households' dietary intake, but also provides hints about the causes of the decline in calorie intake. Nevertheless, this policy improved pastoralist profits and, increased household dietary diversity.

In contrast, private veterinary services and feed program did not significantly improved pastoral profits, although their total effect on dietary diversity is significantly positive. Their indirect effects on the dietary diversity score are nonsignificant and small, while only the direct effect of the feed program on dietary diversity is significant. This suggests that profit is not a good mediator of the effects of these policies, especially for the feed program, or that these policies have too small power for mediation to be apparent.

Let us consider the plausible mechanisms for the direct effects (i.e., nonprofit) of this feed subsidy program. These effects may be conveyed by pastoralist networks or through income sources other than pastoral profits. For example, households may not use the livestock feed they receive to feed their animals, they might rather sell it or give it to their friends or relatives. If they sell it, the received cash may be used to buy food products. If they give it away, they could receive food products in exchange. Therefore, without increasing pastoral profit, the livestock feed program can enhance households' dietary intake by acting as a means of income or an exchange of food products.

Livestock extension services may facilitate household access to livestock products and input markets, and better link the production of animal products and consumption through pastoral profits. However, in terms of modelling approach, given that calories are surely a normal good in this context, the effect of pastoral profit on reducing calorie consumption would rather suggest rejecting separable agricultural household models in favor of complex non-separable mechanisms involving lifestyle changes.

3.5 Conclusion

In this paper, we investigated the effects on household dietary intakes of three national agro-pastoral policies in Niger (livestock extension services, private veterinary services, and subsidies for low-cost livestock feed). We decompose the average treatment effect of each of these policies into an indirect effect—the part of the total effect that passes through the pastoral profit—and a residual direct effect - the part of the total effect that is channeled through other factors.

We have shown results that evinces the diversity of the effects at play for a set of pastoral policies and outcomes in Niger. Some policies (extension services) enjoy significant (positive and negative) average treatment effect on almost all outcomes. Others (veterinary and feed) do not have significant effects on some outcomes (calories). Some outcomes (diet diversity) are improved by all policies, including through agro-pastoral profit. Other outcomes only mostly react to some specific policies, or only through the effects of these policies passing through profit.

Different policy-outcome pairs have different mechanisms and channels. Notably, some insignificant average treatment effects of policies arise from offsetting significant direct and indirect (through profit) effects. This suggests to consider these policies not as a complete failure for the considered outcome, but rather as a complex combination of impacts that could be adjusted to obtain a total significant result later.

Mediation analysis has showed that most of the selected policies in this context have little direct impact beyond their effect through raising profit. Then, one should investigate more closely what their profit-enhancing mechanisms are in order to make them more effective. On the other hand, one could also examine why direct effects (such as through social networks or market functioning) are not more present.

The results show that, while they have no significant direct effects, extension services have a positive and significant indirect effect on household dietary diversity. However, their indirect effect, through pastoral profit, on households' total calorie intake is negative, presumably because households substitute a small rise in calorie intake from animals for a large decline in calorie intake from cereals. By passing through the pastoral profit, extension services foster pecuniary incentives for the specialization of households in pastoral activities, sometimes pushing them toward transhumance or nomadism, a full lifestyle change, which reduces their total calorie consumption since most calories come from cereals. This finding is partially consistent with pastoral profit substantially mediating the impact of livestock extension services on household calorie intake and dietary diversity. In contrast, pastoral profits are not found to mediate the effects of veterinary services and low-cost livestock feed programs on dietary intake. For these policies, other unobserved channels, such as social networks and other income mechanisms, could have affected dietary intake. However, direct effects are never found to be significant, except marginally, at the ten percent level, for the effect of input subsidies on dietary diversity.

Overall, the estimation results show that policies primarily designed to raise pastoral income can substantially, although only partially, contribute to enhancing household dietary diversity and calorie intake from animals for Nigerien pastoralists. However, they may also severely deplete their calorie intake from cereals. To avoid this perverse consequence, policy designers should better account for agro-pastoralists' access to cereal markets and whether the policies generate differentiated incentives in favor of a nomadic or sedentary lifestyle. Indeed, when facing new policies, these households may shift productive activities to specialize in pastoralist activities, which may restrict their access to certain food markets.

The mediation analysis offers specific insights. First, our main policy of interest - that is, livestock extension services - exhibits a high relative contribution of the indirect effects based on profit, while the residual direct effects are nonsignificant. This suggests that policies aimed at raising pastoral profits have significant consequences for dietary intake and therefore for nutritional status. Second, it shows that the direction of these indirect effects on calorie intake is not the one probably intended and that this shortcoming is not offset by negligible direct effects of this policy. Finally, the mediation analysis allows us to understand that the perverse effect of this policy on calorie intake is likely to be related to economic incentives that disrupt joint lifestyle and production choices.

Of course, our findings are dependent on the assumptions made, especially those related to measurement errors in calorie intake data. The typical assumption is that these measurement errors are additive and random, although this assumption may be strong. Another limit to statistical mediation analysis is the possible confusion between changes in the production technology and changes in unobserved inputs when the latter are correlated with observed inputs. Moreover, the exploitation of cross-sectional observational data relies on an ignorability condition, which cannot be tested and may be strong. All these limitations suggest extending this investigation with data from more intensive surveys, in particular those following households over year, so as to get sounder measures of medium term pastoral profit, as shown in Attanasio and Augsburg (2018). Finally, future research, based on richer data, should extend to agricultural mediator variables in addition to pastoral profit and assess other channels through which policies may affect household dietary intake, such as observable changes in activity specialization.

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Conclusion

Dans les régions les plus pauvres du monde, comme le Sahel, la lutte contre la pauvreté a toujours été l'impératif des politiques surtout dans un contexte de croissance démographique, de changement climatique et de hausse accrue de divers risques auxquels font face les ménages. Pour répondre à cet impératif les décideurs politiques réfléchissent continuellement à la mise en place des politiques plus efficaces qui permettront de réduire durablement la pauvreté. Les recherches foisonnantes en économie du développement proposent continuellement des solutions concrètes aux décideurs politiques. Cependant, de nombreuses questions de recherche restent encore en suspens. Cette thèse espère contribuer à éclairer le débat autour de ces enjeux en compilant trois essais empiriques précédemment développés.

Cette thèse a mobilisé des enquêtes ménages, des modèles de la microéconomie et de l'apprentissage automatique pour répondre principalement à trois questions de recherche qui restent encore très inexplorées : (i) Comment les distributions idiosyncratiques des prix alimentaires au niveau des ménages affectent-elles la mesure de la pauvreté monétaire ? (ii) Comment prédire la résilience des ménages avec le plus de précision possible ? (iii) Comment les politiques agricoles affectent-elles l'apport alimentaire des ménages ?

Les trois chapitres qui forment cette thèse ont tenté de répondre à ces questions de recherche, et ont mis en exergue des résultats et recommandations aux décideurs politiques adaptées aux contextes étudiés.

Le chapitre 1 montre que la prise en compte de la distribution idiosyncratique des prix alimentaires au niveau des ménages génère des écarts importants et significatifs dans les indicateurs de pauvreté estimés pour les ménages agropastoraux nigériens. Ce résultat rappelle aux décideurs politiques que la prudence est de mise lorsqu'on utilise des statistiques typiques sur la pauvreté qui ne tiennent pas compte de la dispersion des prix réalisés auxquels chaque ménage est confronté, ce qui est la seule pratique standard actuelle. En effet, une conséquence politique de ces différences est que les priorités de ciblage des régions en termes d'aide alimentaire ou de programmes de transferts en espèces inclus dans les politiques de réduction de la pauvreté seraient inversées entre régions lors du suivi de la pauvreté.

Le chapitre 2 attire l'attention des décideurs politiques sur la nécessité d'utiliser des méthodes plus adaptées pour prédire la résilience des ménages sans quoi, un risque de surestimation du niveau de résilience des ménages et donc une sous-estimation de l'effort à fournir pour construire la résilience des ménages serait à craindre. Enfin, le chapitre 3 montre que l'effet de certaines politiques agricoles sur l'apport alimentaire des ménages en zone rurale passerait par le revenu agricole. Le chapitre 3 attire également l'attention des décideurs politiques sur le fait que certaines politiques peuvent affecter le mode de vie des ménages ce qui dans certains cas serait dommageable pour leurs apports alimentaires.

Même si elle contribue à enrichir les réflexions sur les enjeux de la réduction de la pauvreté des ménages agricoles, cette thèse soulève d'autres questionnements. Notamment, quels sont, sur le plan théorique et empirique, les déterminants des distributions idiosyncratiques des prix au niveau des ménages ? Quels serait l'effet de cette distribution de prix sur l'estimation d'un système de demande ? En dehors du revenu agricole, quels sont les autres canaux par lesquels l'effet des politiques agricoles pourraient passer ? De futurs travaux seront nécessaires pour continuer à appuyer les politiques dans leur lutte contre la pauvreté de manière durable.

Appendix

Appendix A

Appendix to Chapter 1

A1 Construction of the consumption aggregate

As previously stated, the monetary living standard indicator is the household's total consumption value per adult equivalent and per day in real terms. In Niger, it is difficult to obtain accurate data on household income. Instead, in our data, we have information on households' expenditures and consumption. The steps used to compute the total consumption variable are as follows.

A1.1 Database preparation and missing value processing

To construct this aggregate, we needed data on prices and quantities for each product consumed by the household. In the database, the quantities of food consumed by households had sometimes been evaluated in local units of measurement (*lum*), for which the equivalent levels in kgs or liters had been calculated. The same applies to the prices given by *lum*. One initial task therefore consisted of converting these quantities into kgs or liters and prices into CFA/kg or CFA/liter.

However, for some *lum*, the equivalent conversion rates were missing. These missing *lum* values were replaced as follows. First, *lums* were divided into two categories: *lums* that we call "conventional", such as 50 kg or 100 kg bags and a 25 g pack of millet, and "nonconventional" lums that are local, such as tia and tongolo. The latter are often used as weighting measures for the purchase of cereals in local markets in West Africa. The equivalent rates for "conventional" *lum* are known and standardized. On the other hand, for the "nonconventional" *lum*, we used equivalent rates provided in the database. Given that for this type of *lum*, the equivalent rates in kg or in liter vary across regions, we built a database containing, for each of these *lum*, equivalent rates by geographical zone (region, department, commune, and locality or village). In practice, we retained the smallest geographical level for which we had a sufficient number of observations of equivalent rates. Then, for each *lum*, the missing equivalent rates were replaced with the median value of equivalent rates observed for that *lum* in that geographical level to ensure robustness to outliers.

The second task was to deal with the missing values observed for the prices of the consumed goods. Note that the observed prices are purchase prices as stated by households rather than unit values. However, not all of the products consumed by households are purchased at the market. In particular, for these households, some observations on prices are missing.

The algorithm proposed by Muller (2005) to estimate nonmonetary consumption in household surveys was used. For each product and for a given geographical area, the missing values were replaced by the median value of all its observed purchase prices. The procedure started with the village level, the lowest geographical level, assuming that households belonging to the same village are likely to face the same purchase prices. At the village level, the median was calculated for a given product using samples of prices with at least 10 observations. If at the village level, there are fewer than 10 observations, one moved to the next higher geographical level, which is the commune, and the same procedure is repeated. When the constraint of the minimal number of price observations was not satisfied, one moved to the next upper geographical level, thus neglecting the price variation at this geographical scale. If, finally, at the highest scale, the regional level, one cannot replace all the missing or zero values, the constraint on the number of observations is relaxed by making it less than 10.

The following table shows the outcome of this algorithm for the products used to compute the price index and for each season. As shown in this table, the percentage of households for which missing price values have been replaced by median values varies between 5 percent and 71 percent depending on the type of product and the season. Moreover, in most cases, missing values have been replaced with median price values at the regional level, a geographical level for which there is a sufficient number of observations. Note that village or communal replacement would often fit the typical practices to generate price data well. However, it seems reasonable to consider that the gaps identified in this paper due to the differences between minimal and maximal prices should be seen as conservative, as some of these differences may be attenuated by the aggregation process used in this algorithm.

Table A1: Percentage of Seasonal Prices Replaced by the Median Values by Area Type for the Minimum and Maximum Prices

Products	Cold and dry season					Hot and dry season					Rainy season				
	V	C	D	R	All	V	C	D	R	All	V	C	D	R	All
Millet	8.08	28.95	11.33	9.17	**57.53**	7.07	23.32	6.5	5.99	**42.88**	6.86	28.01	8.95	6.21	**50.03**
Sorghum	0.86	6.71	5.85	58.3	**71.72**	0.72	17.72	8.80	40.9	**68.14**	1.66	14.3	5.63	42.82	**64.41**
Cowpea	2.02	4.04	1.08	57.25	**64.39**	1.01	10.61	1.15	51.19	**63.96**	1.37	10.83	5.41	45.48	**63.09**
Maize	0.14	0.21	12.27	37.03	**49.65**	0.14	7.5	8.95	42.23	**58.82**	0.5	4.33	13.2	28.88	**46.91**
Groundnut	0	0	0	49.89	**49.89**	0	0	0	50.10	**50.10**	0	0	0	49.89	**49.89**
Butter	0	0	0	19.20	**19.20**	0	0	0	5.04	**5.04**	0	0	0	38.62	**38.62**
Kola nut	0.07	5.41	0	51.33	**56.81**	0.14	5.41	0	51.55	**57.1**	0.14	5.48	0	51.33	**56.95**
Okra	0.72	4.47	2.38	46.42	**53.99**	0.28	4.25	2.45	46.64	**53.62**	0.64	3.97	2.52	33.28	**40.41**
Oil	1.73	5.48	5.34	13.72	**26.27**	2.16	8.23	4.90	7.65	**22.94**	1.66	7.14	4.18	15.88	**28.86**
Fresh milk	0.28	4.25	0	40.57	**45.1**	0.07	4.54	0	22.23	**26.84**	0.36	4.40	0	29.45	**34.21**
Curdled milk	0.86	11.84	2.16	18.98	**33.84**	0.64	8.59	2.31	23.68	**35.22**	0.64	12.12	2.16	18.19	**33.11**
Bread	0	0	0	28.30	**28.30**	0	0	0	28.51	**28.51**	0	0	0	28.51	**28.51**
Pasta	0.5	5.63	1.66	30.32	**38.11**	0.43	6.13	1.44	30.54	**38.54**	0.5	6.42	1.66	30.03	**38.61**
Fish	0	0	0	29.96	**29.96**	0	0	0	10.25	**10.25**	0	0	0	17.54	**17.54**
Sugar	1.73	6.85	2.52	11.55	**22.65**	1.87	5.27	5.19	11.69	**24.02**	1.80	9.09	2.52	8.44	**21.85**
Tobacco	0.144	1.29	0	36.75	**38.18**	0.14	1.29	0	36.67	**38.1**	0.14	1.29	0	36.75	**38.18**
Tea	1.37	5.99	0	19.35	**26.71**	1.22	6.71	0	19.56	**27.49**	1.22	6.71	0	19.13	**27.06**
Condiments	0.64	3.17	6.93	3.68	**14.42**	0.72	3.10	6.85	3.68	**14.35**	0.43	3.97	7.0	3.89	**15.29**
Meat	0.21	5.27	3.46	14.15	**23.09**	0.28	5.12	3.24	15.02	**23.66**	0.36	5.55	3.24	14.22	**23.37**
Poultry	0.28	0	0	24.83	**25.11**	0.07	0	0	6.64	**6.71**	0.14	0	0	14.44	**14.58**

Notes: Values presented in this table are in percent. They represent the proportion of missing values replaced with the median price value at the village (V), communal (C), departmental (D) and regional (R) levels. "All" is the total of these proportions for a given product.

A1.2 Goods included in the consumption aggregate

All food products are included in the consumption aggregate for each household. For nonfood products, following the recommendations of Deaton and Zaidi (2002), health expenditures are excluded, but expenditures on water, energy, telecommunications, transportation, education, and personal care are included. Finally, transitory expenses, such as for holidays or ceremonies, are not included in the aggregate.

The food consumption expenditure is evaluated for each season and alternatively with the minimum and maximum prices faced by each household. The nonfood expenses are given for the whole year, and therefore, they were divided by three to estimate their value for each of the three seasons. Finally, the total consumption aggregate for each season is obtained by adding up food consumption expenditure and nonfood expenses. The annual consumption aggregate for a given household is therefore the sum of its three seasonal consumption aggregates. The value of the consumption aggregates, in each case, was calculated using alternatively minimum and maximum food prices. Then, they were deflated with the Laspeyres price index calculated at the household level and with an equivalent scale that reflects the household demographic composition.

A1.3 The price index and the equivalence scale

Laspeyres price indices were calculated for each of the three seasons as in Muller (2008). In the basket of goods used to calculate them, we kept only those products (mainly food) for which the number of price observations was at least 20, as suggested by Deaton and Tarozzi (2000). The food price index (FPI) was calculated at the household level.

$$FPI_{it} = \sum_g S^g \times (p^g_{it}/P^g_t), \text{ where } S^g = \frac{\sum_t \sum_i w_i \times p^g_{it} \times q^g_{it}}{\sum_t \sum_g \sum_i w_i \times p^g_{it} \times q^g_{it}} \text{ and } P^g_t = \frac{\sum_i w_i \times p^g_{it}}{\sum_i w_i}$$

S^g is the weight of good g in the price index yearly, w_i is the sample weight of household i, p^g_{it} is the price faced by household i in season t for good g, q^g_{it} is the quantity consumed of good g by household i, and P^g_t is a consistent estimate of the mean price for all consumed quantities of good g at the national level in season t. The household annual price for good g is $p^g_i = \frac{\sum_t q^g_{it} \times p^g_{it}}{\sum_t q^g_{it}}$, which is used to compute the annual FPI. In the FPI formula, the prices are weighted by both sampling weights and consumption quantities. These food price indices are calculated using alternatively the minimum and maximum prices faced by each household.

The adult equivalent variable is computed for each household by using the approach proposed by Deaton and Zaidi (2002). We used the following formula: $AE = NA + 0.67 * NYA + 0.33 * NC$, with AE= Adult Equivalent scale, NA: Number of Adults (>20 years old) in the household, NYA= Number of Young Adults (between 17 and 20 years old) and NC= Number of Children (less than 17 years old).

A2 Descriptive statistics on food prices

Table A2: 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	230.5	15.9	671	239.1	211.7	27.4	671	268	213.3	54.7
		(.639)	(.643)	(.907)		(.310)	(.080)	(.320)		(.545)	(.076)	(.550)
Sorghum (kg)	671	187	163.8	23.2	671	227.9	208.9	19	671	230.3	210.1	20.3
		(.080)	(.069)	(.105)		(.383)	(.383)	(.542)		(.077)	(.068)	(.103)
Cowpea (kg)	671	342	309.8	32.2	671	361.8	318.6	43.2	671	378.9	333.3	45.6
		(.289)	(.256)	(.387)		(.416)	(.259)	(.491)		(.234)	(.196)	(.306)
Maize (kg)	559	197.6	188	9.6	671	244.6	227.5	17.1	559	242.2	217	25.2
		(.083)	(.068)	(.108)		(.161)	(.079)	(.180)		(.324)	(.078)	(.334)
Groundnut (kg)	470	440.5	390.9	49.6	470	472.9	383.4	89.5	470	604.5	470.5	134
		(.290)	(.286)	(.408)		(.161)	(.200)	(.257)		(1.21)	(.245)	(1.23)
Butter (kg)	402	1301.4	1024.2	277.3	275	1563.9	1157	406.9	387	1309.8	1002.9	306.6
		(.714)	(.377)	(.807)		(1.37)	(.755)	(1.57)		(.936)	(.908)	(1.30)
Kola nut (kg)	630	561.2	506.7	54.4	630	501.1	377.5	123.6	630	590.6	451.3	139.2
		(2.36)	(2.25)	(3.27)		(1.90)	(1.45)	(2.39)		(2.35)	(1.80)	(2.96)
Okra (kg)	630	967.5	781.5	185.9	630	1075.7	938.7	136.9	503	1161	984	177
		(1.03)	(.89)	(1.37)		(1.27)	(1.07)	(1.66)		(1.88)	(1.58)	(2.46)
Oil (l)	671	869.6	802.6	67.1	671	882.5	779.2	103.2	671	902.6	803.8	98.8
		(.641)	(.466)	(.792)		(1.23)	(.477)	(1.32)		(.908)	(.469)	(1.02)
Fresh milk (l)	514	362.3	288.9	73.4	514	455.1	334.8	120.3	597	417.1	296.5	120.7
		(.470)	(.202)	(.512)		(.348)	(.278)	(.446)		(.273)	(.177)	(.325)
Curdled milk (l)	630	312.5	235.8	76.7	597	373.71	343.1	30.6	630	453	310.5	142.4
		(.941)	(.647)	(1.14)		(2.28)	(2.28)	(3.23)		(4.48)	(2.26)	(5.02)
Bread (kg)	630	350.8	304.9	45.9	630	394.5	342	52.5	630	378.6	331.4	47.3
		(.330)	(.311)	(.453)		(.510)	(.485)	(.704)		(.464)	(.404)	(.615)
Pasta (kg)	671	520.8	467.1	53.7	671	522.4	468.8	53.6	671	526.3	469.4	56.9
		(.369)	(.318)	(.487)		(.371)	(.319)	(.489)		(.359)	(.320)	(.481)
Fish (kg)	559	1299.5	1080.6	218.9	559	917.1	774.2	142.9	518	1306.4	1110.7	195.7
		(1.69)	(1.45)	(2.23)		(1.45)	(1.14)	(1.85)		(2.15)	(1.87)	(2.85)
Sugar (kg)	671	617.8	555.7	62.1	671	602.5	541.1	61.4	671	632.1	570.9	61.2
		(.472)	(.428)	(.637)		(.456)	(.420)	(.620)		(.625)	(.414)	(.750)
Tobacco (kg)	638	2012.9	1665.8	347.1	638	1971.7	1767.4	204.3	638	2994.6	2520.9	473.7
		(3.54)	(2.60)	(4.40)		(3.37)	(2.50)	(4.20)		(5.71)	(4.47)	(7.26)
Tea (kg)	671	1018.6	883.1	135.5	671	1089.3	907.5	181.9	671	1078	942.7	135.3
		(2.65)	(2.07)	(3.36)		(2.49)	(1.97)	(3.18)		(2.08)	(1.92)	(2.83)
Condiments (kg)	671	1014.4	880.9	133.5	671	1040.9	924.8	116.1	671	1046.8	914.1	132.7
		(2.22)	(1.68)	(2.79)		(2.07)	(1.78)	(2.73)		(2.03)	(1.74)	(2.68)
Meat (kg)	671	1932.3	1560.9	371.5	671	1958.6	1713.7	244.9	671	1981.8	1730.6	251.2
		(2.09)	(1.52)	(2.58)		(2.03)	(1.72)	(2.67)		(1.87)	(1.68)	(2.52)
Poultry (kg)	638	2100.7	1513.7	587	638	1987.8	1441.7	546.1	638	2123	1527.6	595.4
		(2.58)	(1.37)	(2.92)		(2.57)	(1.34)	(2.90)		(2.45)	(1.32)	(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.

A3 Estimated absolute poverty line

The poverty line is calculated in five steps that follows a usual method implemented by the World Bank worldwide. These steps are replicated with each of the three seasonal living standards and the annual real living standards to estimate seasonal and chronic poverty measures, respectively. Moreover, these steps in each case are applied alternatively with minimum and maximum prices. A total of 8 poverty lines are therefore estimated.

A3.1 Defining a reference group of poor households

A reference group was constructed on the basis of the distribution of the real living standard per adult equivalent. This group is used to ensure that the consumption patterns employed for defining the poverty line are not overly influenced by those of wealthy households. This group corresponds to the lowest half of the distribution. This is consistent with nearly 42 percent of the population being considered officially poor (Institut National de la Statistique and Banque Mondiale, 2013). We regrouped the seven regions into two categories: the South (formed by Dosso, Tahoua and Tillaberi regions) and the North (formed by Agadez, Diffa, Maradi and Zinder). This distinction allows for better control of the geographical variations in household consumption habits. Thus, the reference groups are constituted separately for the North and the South, and their union represents the reference group for the whole country.

A3.2 Defining the caloric need for households belonging to the reference group

The caloric intake per capita per day for each household is computed by converting the recorded food quantity consumed by the household over the year into calories. For this conversion, the FAO food composition table for West Africa in 2012 was used (Stadlmayr et al., 2012). Calories requirements for households in this reference group, in each stratum, are specified as 2700 Kcal per day and per adult to account for moderate activity level. The National Institute of Statistics of Niger instead uses an energy requirement of 2400 Kcal/day per individual. However, we want to account for the typically relatively higher activity level of agropastoral households that are not fully sedentary.

The 2700 Kcal requirement per day per adult is then multiplied by the average equivalent scale in the reference group and divided by the corresponding average household size. This adjustment allows us to account for nutritional requirements increasing with the age and gender of household members.

The mean unit price of the calories consumed in each stratum for the reference group is then calculated as the ratio of the average value of food consumption in the reference group to its average calorie intake.

A3.3 Defining the food poverty line

The food poverty line is the minimum income needed for a household to have access to the calories required for an active life. Based on the unitary price of calories consumed by a household in the reference group and his energy requirement, the calculus of the food poverty line is the value of the calorie requirement. The food poverty line is calculated for each of the two strata (North and South).

A3.4 Defining the absolute poverty line

The absolute poverty line is obtained by extrapolating the food poverty line to the whole range of consumption. This process allows for the inclusion of nonfood consumption by using a food Engel curve, which is consistent with the quadratic almost ideal demand system. The estimated Engel curve equation is:

$$s_i = a + b \times \ln(x_i) + c \times \ln(x_i)^2 + d \times N_i + \varepsilon_i$$

where s_i is the share of food expenditure in the total expenditure of household i, x_i is its daily real total consumption, N_i are household sociodemographic characteristics, and ε_i is an error term. The coefficients a, b, c, and d are estimated by the ordinary least squares method, as is typical in the World Bank methodology. Also, since the main source of ignorance in the estimation of the poverty line is the individual heterogeneity, there is no weighing by the sampling scheme here. However, we checked that weighing by the sampling scheme did not substantially change the estimated poverty line. The estimation results are shown below.

Two different equations have been estimated separately for the North and the South. The absolute poverty line z_j for stratum j is obtained by replacing s_i with the ratio of the food poverty line by $z_j$and solving numerically in $z_j$the following equation of the estimated Engel curve:

$\frac{z_j^f}{z_j} = a_j + b \times \ln\left(z_j\right) + c \times \ln\left(z_j\right)^2$, where z_j^f is the computed food poverty line in stratum j for the whole household (i.e., the previously computed food poverty line is multiplied by the average household size of the corresponding reference group in stratum j). The fixed effects a_j account for the different mean values of other independent variables in the North and the South. The absolute poverty line in stratum j, z_j, is obtained by solving the above equation with the bisection method. The value obtained is then divided by the mean adult equivalent scale of the reference group of stratum j, which makes the poverty line comparable to the specified real living standards. Alternatively, the real living standards of the reference group could be readjusted by using the estimated Engel curve to attempt to account for unobserved non-food prices in the deflation. Then, the process can be iterated with new estimates of the Engel curve, until convergence, if the latter occurs. This is inspired from the procedure in Pradhan et al. (2001). However, as this procedure is typically not employ for poverty studies in national statistical offices, we refrain from this extension.

Table A3: Estimated Engel curve

	S_i					
Variables	National level (N=671)		North (N=284)		South (N=387)	
	Pmin	Pmax	Pmin	Pmax	Pmin	Pmax
$\ln(x_i)$	.740***	.713***	.753**	.773*	.697***	.654***
	(.201)	(.186)	(.378)	(.398)	(.144)	(.120)
$\ln(x_i)^2$	-.046***	-.043***	-.048*	-.048*	-.042***	-.039***
	(.014)	(.013)	(.026)	(.027)	(.009)	(.007)
$\ln(AE)$	-.055***	-.048***	-.033	-.035	-.068***	-.057***
	(.015)	(.014)	(.026)	(.028)	(.017)	(.016)
Area of living: 1 if in the South and 0 otherwise	.029**	.035**	-	-	-	-
	(.013)	(.014)				
Constant	-1.97***	-1.92***	-2.00	-2.13	-1.82***	-1.68***
	(.695)	(.65)	(1.29)	(1.39)	(.548)	(.465)

Notes: Values in parentheses are standard errors. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

A3.5 Descriptive statistics on Food Expenditure and Laspeyres' Food Price Index

Table A4: Nominal Food Expenditure and Laspeyres' Food Price Index using Alternative Prices

Variables	Prices	Cold and dry season (N=671)		Hot and dry season (N=671)		Rainy season (N=671)		Year (N=671)	
		Mean	Std	Mean	Std	Mean	Std	Mean	Std
Food expenditure (CFA/day/adult equivalent)	Pmax	588.82	1223.70	509.71	892.87	639.14	1139.39	579.23	960.55
	Pmin	527.21	1144.21	455.53	869.19	520.26	971	501	896.13
	R.Diff	.140	.209	.143	.458	.246	.794	.173	.303
Food price index	Pmax	1.00	.504	.977	.258	1.017	.595	.921	.701
	Pmin	1.01	.529	.986	.211	1.00	.230	.917	.674
	R.Diff	.001	.092	-.009	.164	.008	.501	.015	.270
Real food expenditure (CFA/day/adult equivalent)	Pmax	583.51	1390.77	530.81	1106.76	656.73	1423.58	768.07	1957.05
	Pmin	509.41	1228.75	466.51	1032.36	535.98	1253.65	665.28	1722.24
	R.Diff	.137	.102	.145	.206	.230	.186	.161	.117

Notes: The mean values presented in the table are sample means. The three seasonal food expenditures are summed to obtain their annual values. The base of the seasonal food price indices is the mean national price of the corresponding season. The annual food price index is computed using the weighted average of seasonal food prices, where the weights indicate the quantity of food consumed by the household. For the seasonal food price indices, the base of the annual food price index is the national average price of the year. Pmin=Minimum prices, Pmax=Maximum prices, R. Diff= Relative difference between the minimum and maximum prices.

A3.6 Estimated Poverty Lines

Table A5: Seasonal Food and Absolute Poverty Lines in Real Terms (CFA/day/adult equivalent)

Poverty lines	Geographic location	Cold and dry season		Hot and dry season		Rainy season		Year	
		Pmin	Pmax	Pmin	Pmax	Pmin	Pmax	Pmin	Pmax
Food poverty line	North	107.7	121.2	130.2	142.1	130.8	151.7	118.6	134.6
	South	138.7	150.2	137.5	150.8	160.7	197.4	140.4	162.4
	National	124.9	137.2	134.5	147.1	147.5	176.9	130.8	150
Absolute poverty line	North	219.7	246.8	260.6	284.5	261.7	301.7	239.6	270.9
	South	241.8	259.7	240	260.6	276.2	333.2	244.5	278.7
	National	232.5	254.2	248.8	270.7	270.1	319.9	242.4	275.4

Notes: Pmin=Minimum prices, Pmax=Maximum prices. The national poverty line is composed of the two regional poverty lines and considers the value of the North poverty line if the household lives in the North and the South poverty line if the household lives in the South. The national poverty line presented in this table is the mean of the national poverty line.

A4 Effects of Households characteristics on Food Price Index

Table A6: For the Cold and Dry Season

VARIABLES	(1) **Log of Minimum Food Prices Index**	(2) **Log of Maximum Food Prices Index**
Sex of HH, 1 if male	0.003	0.009
	(0.018)	(0.020)
Age of HH	-0.000	-0.000
	(0.000)	(0.000)
Household Size	-0.001	0.000
	(0.001)	(0.002)
HH is Haoussa	0.017	0.021
	(0.047)	(0.054)
HH is Fulani	-0.001	-0.008
	(0.035)	(0.041)
HH is Touareg	0.021	0.024
	(0.037)	(0.042)
H. live in a Hamlet	-0.060	-0.056
	(0.103)	(0.119)
H. live in a Village	-0.111	-0.113
	(0.118)	(0.136)
Constant	0.023	0.015
	(0.094)	(0.109)
Observations	666	666
R-squared	0.004	0.004
Number of localities	79	79
Locality FE	YES	YES

Notes: Standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. HH: Household head, H: Household

Table A7: For the Hot and Dry Season

VARIABLES	(1) Log of Minimum Food Prices Index	(2) Log of Maximum Food Prices Index
Sex of HH, 1 if male	0.003	0.016
	(0.018)	(0.023)
Age of HH	-0.000	-0.000
	(0.000)	(0.000)
Household Size	-0.000	0.001
	(0.001)	(0.002)
HH is Haoussa	0.035	0.037
	(0.046)	(0.060)
HH is Fulani	0.017	0.018
	(0.035)	(0.045)
HH is Touareg	0.029	0.037
	(0.037)	(0.047)
H. live in a Hamlet	-0.056	-0.056
	(0.103)	(0.132)
H. live in a Village	-0.232**	-0.227
	(0.118)	(0.152)
Constant	0.106	0.066
	(0.094)	(0.121)
Observations	666	666
R-squared	0.020	0.013
Number of localities	79	79
Locality FE	YES	YES

Notes: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. HH: Household head, H: Household

Table A8: For the Rainy Season

VARIABLES	(1) Log of Minimum Food Prices Index	(2) Log of Maximum Food Prices Index
Sex of HH, 1 if male	0.008	0.018
	(0.013)	(0.031)
Age of HH	-0.000	-0.001
	(0.000)	(0.001)
Household Size	0.000	0.000
	(0.001)	(0.002)
HH is Haoussa	0.038	0.011
	(0.034)	(0.080)
HH is Fulani	0.025	0.000
	(0.026)	(0.061)
HH is Touareg	0.043	0.013
	(0.027)	(0.063)
H. live in a Hamlet	-0.024	-0.030
	(0.076)	(0.177)
H. live in a Village	-0.096	-0.105
	(0.087)	(0.203)
Constant	0.009	0.049
	(0.069)	(0.162)
Observations	666	666
R-squared	0.011	0.007
Number of localities	79	79
Locality FE	YES	YES

Notes: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. HH: Household head, H: Household

A5 Living Standards Distribution

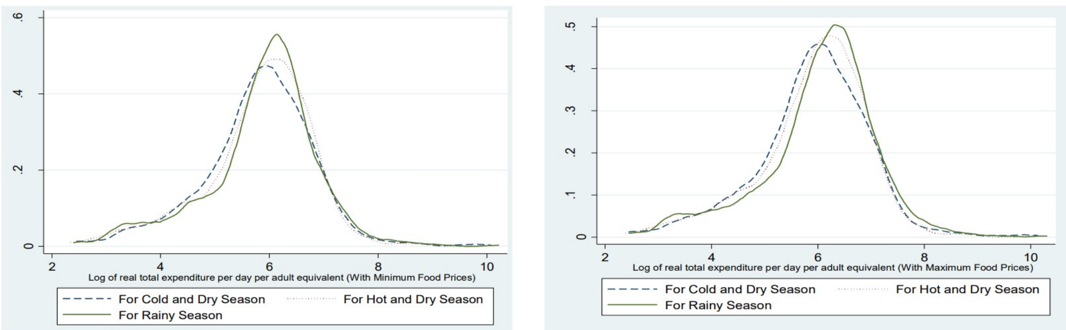


Figure A1: Living Standards Distribution

Appendix B

Appendix to Chapter 2

B1 Descriptive statistics

Variables	Wave 1 (2010/2011)		Wave 2 (2012/2013)		Wave 3 (2015/2016)	
	PP (N=3,432)	PH (N=3,432)	PP (N=3,432)	PH (N=3,432)	PP (N=3,432)	PH (N=3,432)
Outcome variable						
Daily real total expenditure per capita (Naira)	398.33 (306.86)	454.95 (374.52)	424.44 (357.42)	376.97 (302.06)	447.07 (445.50)	367.13 (316.02)
Household is poor at International Poverty Line (1 if yes, 0 otherwise)	0.25 (0.43)	0.21 (0.40)	0.22 (0.41)	0.26 (0.44)	0.25 (0.43)	0.31 (0.46)
Household is poor at National Poverty Line (1 if yes, 0 otherwise)	0.39 (0.49)	0.35 (0.48)	0.37 (0.48)	0.44 (0.49)	0.40 (0.49)	0.47 (0.50)
HH characteristics						
HH head is female (1 if yes, 0 otherwise)	0.14 (0.35)	0.14 (0.35)	0.14 (0.35)	0.14 (0.35)	0.14 (0.35)	0.14 (0.35)
HH live in rural area (1 if yes, 0 otherwise)	0.72 (0.45)	0.72 (0.45)	0.72 (0.45)	0.72 (0.45)	0.72 (0.45)	0.72 (0.45)
HH head is monogamous (1 if yes, 0 otherwise)	0.62 (0.49)	0.63 (0.48)	0.64 (0.48)	0.60 (0.49)	0.60 (0.49)	0.60 (0.49)
HH head is polygamous (1 if yes, 0 otherwise)	0.20 (0.40)	0.20 (0.40)	0.18 (0.39)	0.22 (0.41)	0.22 (0.41)	0.22 (0.41)
HH head is widowed (1 if yes, 0 otherwise)	0.12 (0.33)	0.12 (0.33)	0.13 (0.33)	0.13 (0.34)	0.14 (0.34)	0.14 (0.35)
HH head is Christian (1 if yes, 0 otherwise)	0.52 (0.5)	0.52 (0.5)	0.52 (0.5)	0.52 (0.5)	0.52 (0.5)	0.52 (0.5)
HH head is Muslim (1 if yes, 0 otherwise)	0.46 (0.5)	0.46 (0.5)	0.46 (0.5)	0.46 (0.5)	0.46 (0.5)	0.46 (0.5)
Age of HH head in years	48.75 (14.33)	49.88 (35.46)	51.17 (14.43)	51.56 (14.39)	53.86 (14.26)	53.99 (14.20)
HH head is in agricultural activity (1 if yes, 0 otherwise)	0.73 (0.45)	0.73 (0.45)	0.70 (0.46)	0.70 (0.46)	0.72 (0.45)	0.72 (0.45)
HH head has a higher education level (1 if yes, 0 otherwise)	0.01 (0.12)	0.01 (0.12)	0.02 (0.12)	0.02 (0.12)	0.02 (0.12)	0.02 (0.12)
HH head has no education (1 if yes, 0 otherwise)	0.32 (0.47)	0.32 (0.47)	0.33 (0.47)	0.33 (0.47)	0.34 (0.47)	0.34 (0.47)
HH head has a primary education level (1 if yes, 0 otherwise)	0.31 (0.46)	0.31 (0.46)	0.29 (0.46)	0.29 (0.46)	0.29 (0.45)	0.29 (0.45)
HH head has a secondary education level (1 if yes, 0 otherwise)	0.23 (0.42)	0.23 (0.42)	0.24 (0.43)	0.24 (0.43)	0.23 (0.42)	0.23 (0.42)
HH demographics						
Proportion of female members with age 66 years old	0.03 (0.13)	0.03 (0.13)	0.03 (0.14)	0.03 (0.14)	0.03 (0.14)	0.03 (0.13)
Proportion of male members with age 66 years old	0.02 (0.09)	0.02 (0.09)	0.03 (0.10)	0.03 (0.10)	0.03 (0.10)	0.03 (0.10)
Proportion of female members with age between 16 and 65 years old	0.28 (0.18)	0.28 (0.18)	0.26 (0.17)	0.27 (0.17)	0.24 (0.16)	0.23 (0.15)
Proportion of male members with age between 16 and 65 years old	0.26 (0.21)	0.25 (0.20)	0.24 (0.19)	0.24 (0.19)	0.21 (0.17)	0.21 (0.17)
Proportion of female members with age between 5 and 15 years old	0.12 (0.14)	0.12 (0.14)	0.11 (0.13)	0.12 (0.14)	0.11 (0.13)	0.11 (0.13)
Proportion of male members with age between 5 and 15 years old	0.13 (0.15)	0.13 (0.14)	0.13 (0.14)	0.13 (0.14)	0.12 (0.13)	0.12 (0.13)
Proportion of female members with age between 0 and 4 years old	0.07 (0.11)	0.07 (0.12)	0.06 (0.10)	0.06 (0.10)	0.04 (0.08)	0.04 (0.08)
Proportion of male members with age between 0 and 4 years old	0.07 (0.12)	0.08 (0.12)	0.06 (0.10)	0.06 (0.10)	0.05 (0.09)	0.05 (0.08)

B2 Descriptive statistics-Continued

Variables	Wave 1 (2010/2011)		Wave 2 (2012/2013)		Wave 3 (2015/2016)	
	PP (N=3,432)	PH (N=3,432)	PP (N=3,432)	PH (N=3,432)	PP (N=3,432)	PH (N=3,432)
HH shocks						
Death of an adult working member (1 if yes, 0 otherwise)	0.06 (0.24)	0.06 (0.24)	0.07 (0.25)	0.07 (0.25)	0.04 (0.19)	0.04 (0.19)
Illness of income earning member (1 if yes, 0 otherwise)	0.04 (0.19)	0.04 (0.19)	0.05 (0.23)	0.05 (0.23)	0.03 (0.16)	0.03 (0.16)
Poor rain (1 if yes, 0 otherwise)	0.05 (0.21)	0.05 (0.21)	0.03 (0.17)	0.03 (0.17)	0.04 (0.19)	0.04 (0.19)
Flooding (1 if yes, 0 otherwise)	0.03 (0.17)	0.03 (0.17)	0.09 (0.28)	0.09 (0.28)	0.03 (0.18)	0.03 (0.18)
Death of livestock (1 if yes, 0 otherwise)	0.03 (0.16)	0.03 (0.16)	0.02 (0.14)	0.02 (0.14)	0.02 (0.13)	0.02 (0.13)
Increase in input prices (1 if yes, 0 otherwise)	0.03 (0.18)	0.03 (0.18)	0.02 (0.16)	0.02 (0.16)	0.04 (0.20)	0.04 (0.20)
Increase in food prices (1 if yes, 0 otherwise)	0.06 (0.23)	0.06 (0.23)	0.06 (0.24)	0.06 (0.24)	0.14 (0.35)	0.14 (0.35)
Shocks at community level						
Drought event in the community (1 if yes, 0 otherwise)	0.21 (0.40)	0.21 (0.40)	0.11 (0.31)	0.11 (0.31)	0.16 (0.37)	0.16 (0.37)
Flood event in the community (1 if yes, 0 otherwise)	0.26 (0.44)	0.26 (0.44)	0.40 (0.49)	0.40 (0.49)	0.26 (0.44)	0.26 (0.44)
Crop disease event in the community (1 if yes, 0 otherwise)	0.28 (0.45)	0.28 (0.45)	0.19 (0.39)	0.19 (0.39)	0.15 (0.36)	0.15 (0.36)
Livestock disease event in the community (1 if yes, 0 otherwise)	0.20 (0.40)	0.20 (0.40)	0.12 (0.32)	0.12 (0.32)	0.08 (0.27)	0.08 (0.27)
Sharp change in prices event in the community (1 if yes, 0 otherwise)	0.43 (0.5)	0.43 (0.5)	0.44 (0.5)	0.44 (0.5)	0.52 (0.5)	0.52 (0.5)
Development project event in the community (1 if yes, 0 otherwise)	0.20 (0.40)	0.20 (0.40)	0.25 (0.43)	0.25 (0.43)	0.32 (0.47)	0.32 (0.47)
Geographic variables						
HH distance to nearest major road (km)	14.4 (17.61)	14.4 (17.61)	14.4 (17.61)	14.4 (17.61)	14.4 (17.61)	14.4 (17.61)
HH distance to nearest market (km)	68.53 (42.91)	68.53 (42.91)	68.53 (42.91)	68.53 (42.91)	68.53 (42.91)	68.53 (42.91)
Annual mean temperature (^{o}C*10)	263.67 (9.48)	263.67 (9.48)	263.70 (9.39)	263.70 (9.39)	263.69 (9.39)	263.69 (9.39)
Annual precipitation (mm)	1425.33 (620.39)	1425.33 (620.39)	1425.37 (620.49)	1425.37 (620.49)	1425.23 (620.10)	1425.23 (620.10)
Terrain roughness: HH live in high altitude plains (1 if yes, 0 otherwise)	0.11 (0.31)	0.11 (0.31)	0.10 (0.31)	0.10 (0.31)	0.10 (0.31)	0.10 (0.31)
Terrain roughness: HH live in lowlands (1 if yes, 0 otherwise)	0.13 (0.33)	0.13 (0.33)	0.12 (0.33)	0.12 (0.33)	0.13 (0.34)	0.13 (0.34)
Terrain roughness: HH live in mid altitude plains (1 if yes, 0 otherwise)	0.28 (0.45)	0.28 (0.45)	0.29 (0.45)	0.29 (0.45)	0.28 (0.45)	0.28 (0.45)
Terrain roughness: HH live in plains (1 if yes, 0 otherwise)	0.30 (0.46)	0.30 (0.46)	0.31 (0.46)	0.31 (0.46)	0.30 (0.46)	0.30 (0.46)
Terrain roughness: HH live in very low plateaus (1 if yes, 0 otherwise)	0.12 (0.33)	0.12 (0.33)	0.12 (0.33)	0.12 (0.33)	0.13 (0.34)	0.13 (0.34)

Notes: Mean values are presented, and standard deviations are in parentheses. 1$PPP=101.91 Naira. The International poverty line is 1.90$PPP per capita per day. The National poverty line is equal to 376.52 per capita per day in 2019 (National Bureau of Statistics, 2020), which corresponds to 258.85 2016 constant Naira, and 2.54 $ PPP per capita per day.

B3 Training of the Neural Network to estimate the parameters of the Gaussian Mixture Model

A Neural Network (NN) with two dense layers of 200 neurons is constructed to estimate the parameters of a mixture of five Gaussian distributions. The target variable is the log of household real total consumption expenditure per capita and per day. The NN is fed with the 43 independent variables presented in sections A1 and A2 of the Appendix. We added to these inputs the lagged value of the target variable, its squared and cubed values, following Cissé and Barrett (2018). The NN is trained on four rounds[1] and the last round (PH of Wave 3) was used as test data. From the training set, 20% of the data are held out and used as validation[2] set to finetuned the hyperparameters (number of components, number of dense layers, and the number of neurons in each layer, the learning rate etc..) of the NN. The training was per-

[1]The first round is missing because we computed the lagged values of the target variable.

[2]The size of the training, validation and test sets are 10,982; 2,746 and 3,432, respectively.

formed for 200 epochs with a batch size of 64[3], and a learning rate of 0.001 with an Adam optimizer. To comply with the restriction related to the mixing coefficients, we used, as proposed by Bishop (1994), a *Softmax*[4]activation function[5] to the corresponding network outputs, which forced them to lie in the range (0,1) and sum to unity.

Moreover, to ensure that the variance, representing the scale parameter, is always strictly positive, we used a variant of the Exponential Linear Unit (ELU)[6] with an offset to approximate the exponential behavior, a Non-Negative ELU[7], activation function on the corresponding network outputs (Brando, 2017). We also imposed an additional activity regularization, an L2 regularization, on the variance to prevent them from blowing up. In addition, an L2 regularization was also applied to the weights of the second dense layer to prevent the neural network from overfitting.

The training is implemented in *Tensorflow/Keras*, and all the computations are done using the built-in functions of *Tensorflow* to avoid numerical instability.

B4 Kendall's rank correlation coefficients

International Poverty Line			
	RS- MDN	RS- OLS GLM	Outcome
RS- MDN	1		
RS- OLS GLM	0.82*	1	
Outcome	0.55*	0.56*	1
National Poverty Line			
RS- MDN	1		
RS- OLS GLM	0.82*	1	
Outcome	0.56*	0.57*	1

Notes:* indicates statistical significance at a 1% level. RS-MDN: Resilience score predicted with MDN, RS-OLS&GLM: Resilience score predicted with OLS & GLM. Outcome: Log of total consumption expenditure per capita per day.

[3]One epoch is when the entire dataset is passed forward and backward through the neural network only once, and the batch size is the number of data points used in a single iteration.

[4] $\alpha_i = \frac{\exp(z_i^\alpha)}{\sum_{j=0}^{m-1}\exp(z_j^\alpha)}$ a softmax function where z_i^α are the network outputs for the mixing coefficients.

[5]In a neural network, an activation function defines how the weighted sum of the input is transformed into an output from a node in a layer of the network.

[6] $ELU(z_i^\sigma) = z_i^\sigma, z_i^\sigma > 0; ELU(z_i^\sigma) = c * (\exp(z_i^\sigma) - 1), z_i^\sigma < 0$, where c is a strictly positive parameter.

[7] $ELU(z_i^\sigma) + 1$

Appendix C

Appendix to Chapter 3

C1 Collecting geographical variables at the household level

For each household, we collected annual data on minimum, maximum and average temperatures in degrees Celsius at an altitude of two meters, as well as annual precipitation data measured in millimeters per day from the website for NASA's Prediction of Worldwide Energy Resource Project. The climatic data collected are averaged at the departmental level.

C2 Population of interest

We focus on households that own sheep and cattle. Indeed, first, only the information collected on this group of households is complete enough for econometric analyses. For example, these are the only households for whom we have data on livestock prices, costs and production levels. Another reason to focus on these pastoral and agro-pastoral households is that agro-pastoral policies should not directly affect households that have no pastoral activity. This leaves us with 600 household observations after cleaning the data and removing outliers. In our initial sample, nearly 42 percent of households do not own cattle or sheep, instead they own goats, poultry, donkeys, or camels. When we exclude these households from our initial database, we are left with about 785 households. Then the top 10% of the distribution on calories consumed and pastoral profit were removed. In our final sample, 93 percent of households are agro-pastoralists, while only 7 percent are purely pastoralists. Pastoral households are defined as those that do not usually produce agricultural products and possess a significant number of animals (they are at least medium herders). Moreover, their first, and even second, main activities are livestock production and not agricultural production.

C3 Measurement issues and outliers

Large outliers seem to be related to ceremonies and food stock, although this cannot be fully ascertained. We checked that these outliers are not systematically linked to the absence of policy access. Finally, on average, almost 83 percent of calorie intake comes from cereals, and only 4.4 percent strictly comes from animal food products. It seems likely that calorie intake from animal products has not been fully recorded. In particular, omissions may have occurred due to the 3 months recall period for consumption. The extreme values observed in household calorie consumption data are not necessarily irrelevant outliers. Indeed, a method to detect outliers in univariate data is based on boxplots. However, the distribution of these variables appears to be skewed and long tailed, which makes the standard boxplot method ineffective, as Bruffaerts et al. (2014) pointed out. For this type of data, these authors proposed the generalized boxplot method that deals with these data characteristics (see also Verardi and Vermandele (2018)). Observations identified as outliers with a simple boxplot analysis may not be considered as such with the generalized box plot method.

C4 Construction of variables

We define two distinct types of outcome variables: dietary intake indicators and households' profit from livestock activity. The three treatment variables correspond to the policies selected for this study. Each treatments is described by a dummy variable, which takes a value of 1 when the household reported that it had access to the policy and 0 otherwise.

C4.1 Dietary intake indicators

Two nutrition indicators are constructed: the household *dietary diversity score* and the household *daily calorie intake per capita*. The *dietary diversity score* records how many different food groups had been consumed by the household over a given reference period, and is a good proxy for diet quality. Following the FAO, 12 food groups are used to compute the *dietary diversity score* (Swindale and Bilinsky, 2006). Table 6 shows the food products consumed by the households categorized into the 12 groups.

Table C1: Classification of food products

Food group	**Specific Food Product (from survey)**
A. Cereals	Millet, sorghum, bread, maize, edible pasta
B. Roots and tubers	-
C. Vegetables	Condiments, okra
D. Fruits	-
E. Meat, poultry, offal	Meat, poultry
F. Eggs	-
G. Fish and seafood	Fish,
H. Pulses/legumes/nuts	Cowpea, sesame seeds, groundnuts
I. Milk and milk products	Fresh milk, curdled milk, cheese
J. Oils/Fats	Oil, butter
K. Sugar/honey	Sugar
L. Miscellaneous	Tea

Notes: Classification made by the authors using the food groups proposed by the FAO.

If the household reported that, over the last quarter, it consumed at least one of the food products belonging to a specific food group, an index value of 1 is attributed to this household for the corresponding food group, and 0 otherwise. As can be seen from Table 1, none of the foods consumed by the surveyed households belong to the food groups of roots and tubers, fruits, or eggs. This is because the survey did not record any consumption of these food groups due to their low frequency among agro-pastoralists[1]. Finally, a *dietary diversity score* is computed for each surveyed household as the total unweighted number of food groups consumed by the household.

C4.2 Daily calorie intake per capita

The *daily calorie intake per capita* for each household is computed by converting the recorded food quantity consumed by the household into calories. For this, we use the food composition table provided by the FAO for West Africa in 2012 (Stadlmayr et al., 2012). We separately computed calorie intake coming from cereals (millet, sorghum, bread, maize and edible pasta) and from animal food products (meat, poultry, fish, fresh milk, curdled milk and cheese).

C4.3 Profits from livestock activity

The last outcome variable is the household annual profit from livestock activity. After several attempts, we decided to consider only three outputs: cattle, sheep and milk production (fresh milk and curd), which correspond to the most accurately

[1] In addition to the low frequency issue, the quarterly retrospective questionnaire that has been employed for the survey is likely to generate omissions and thereby lead to underestimated dietary scores.

measured information. For cattle and sheep, we used the animals sold and slaughtered by the household as a measure of output because variations in stocks are unobserved. For milk, we used total household production. There are no data on stock variation for milk production between the two years.

All these production measures were valued at the market prices[2] faced by each household individually. The total of these production values amounts to the gross income of the households from pastoral activity.

For production costs, we were able to track four monetarily valued costs: costs related to the herd's health, livestock water consumption, feed consumption, and labor costs (for shepherds and market middlemen during the sale of animals). These costs are reported by each surveyed household for the whole herd. The (restricted) profit is obtained by subtracting the total observed costs from the obtained gross income. All other unobserved costs and benefits must be omitted, as they were not observed.

C5 Some additional summary statistics

As we can see from Table C2 below, the outcomes of households that have access to a policy generally differ from those that do not. Households who have access to extension services have a calorie intake level that is 42 per cent lower than those who do not. However, their dietary diversity score is 14 percent higher compared to households who do not have access. They also consume more food products from animals and less cereals than those who do not have access to extension services. Households with access to low-cost livestock feed or private veterinary services have a higher dietary diversity score and consume more food products from animals than cereals compared to households who do not have access to these policies. Regarding the annual profit from livestock production, we note that for the three considered policies, those who have access to all these policies are better off than those who do not. These data are therefore suggestive for the analysis that we want to conduct

[2]The cattle and sheep prices are given by animal sex and age. For animals directly consumed by the households, we compute an average price per TLU using these market prices.

Table C2: Comparison of households outcomes based on their access to the policies

	Policies								
	Extension services			Low-cost livestock feed			Private veterinary services		
	No Access	Access	Diff	No Access	Access	Diff	No Access	Access	Diff
Outcomes (mean values)									
Log of total daily per capita calorie intake	7.81 (.05)	7.38 (.14)	.42*** (.14)	7.71 (.06)	7.77 (.12)	-.05 (.15)	7.77 (.06)	7.54 (.10)	.23* (.14)
Log of daily per capita calorie intake from cereals	7.56 (.06)	7.07 (.15)	.50*** (.14)	7.46 (.06)	7.52 (.12)	-.06 (.16)	7.53 (.06)	7.22 (.10)	.30** (.14)
Log of daily per capita calorie intake from animals	3.73 (.08)	3.88 (.19)	-.15 (.19)	3.69 (.08)	4.15 (.18)	-.45** (.21)	3.71 (.08)	3.95 (.17)	-.24 (.19)
Log of household dietary diversity score	1.58 (.02)	1.72 (.02)	-.14*** (.04)	1.57 (.02)	1.80 (.02)	-.23*** (.05)	1.57 (.02)	1.76 (.03)	-.19*** (.04)
Log of annual profit from livestock production	14.69 (.05)	14.96 (.09)	-.26*** (.10)	14.71 (.04)	14.94 (.11)	-.23** (.12)	14.73 (.05)	14.83 (.08)	-.10 (.10)

Notes: Values in parentheses are standard errors. *, ** and *** indicate significance at the 10%, 5% and 1% probability levels, respectively. Column Diff shows the mean difference, for the outcome variable, between the group of households who don't have access to the policy and the group of those who do have access to it.

Table C3: Comparison of pastoral and agropastoral household dietary intake during pastoral mobility

	Agropastoral households (N=557)			Pastoral households (N=43)		
	No Pastoral Mobility (N=444)	Pastoral Mobility (N=113)	Diff	No Pastoral Mobility (N=23)	Pastoral Mobility (N=20)	Diff
Outcomes (mean values of logarithms)						
Total daily per capita calorie intake	7.728 (.062)	7.389 (.136)	.339*** (.141)	9.203 (.072)	7.900 (.185)	1.302*** (.189)
Daily per capita calorie intake from cereals	7.495 (.063)	7.050 (.147)	.445*** (.146)	9.030 (.077)	7.414 (.152)	1.616*** (.164)
Daily per capita calorie intake from animals	3.661 (.091)	3.767 (.183)	-.105 (.202)	4.107 (.264)	5.679 (.419)	-1.571*** (.527)
Household dietary diversity score	1.570 (.021)	1.704 (.030)	-.133*** (.045)	1.628 (.056)	1.963 (.033)	-.335*** (.068)
Annual profit from livestock production	14.606 (.048)	15.001 (.080)	-.395*** (.103)	15.067 (.135)	16.181 (.282)	-1.114*** (.300)

As shown in Table C4, households' assessment depends on where they live. Indeed, households living in the South of the country seem to have easier physical access to livestock extension services than those living in the North. In fact, the proportion of households that had access to this policy and that considered the policy easily accessible is significantly higher for households living in the South than for those in the North. However, the opposite situation is observed for private veterinary service, where access seems to be easier for households living in the North than for those in the South. On the other hand, for these two policies, there is no significant difference between North and South in terms of households' evaluation of cost. It is only the assessment of the cost of the low-cost livestock feed service that is significantly different; namely, it is considered to be cheaper in the South than in the North.

Table C4: Households' assessment of the policies

Assessed aspects	Policies	North (N=239)	South (N=361)	Difference
Physical accessibility (1 if easy and 0 otherwise)	Livestock extension services	.555 (.082) [36]	.734 (.048) [83]	-.179** (.095)
	Low-cost livestock feed	.512 (.080) [39]	.480 (.069) [52]	.032 (.105)
	Private veterinary services	.753 (.051) [69]	.615 (.067) [52]	.138* (.085)
Cost (1 if less expensive and 0 otherwise)	Livestock extension services	.805 (.065)	.807 (.043)	-.001 (.078)
	Low-cost livestock feed	.871 (.053)	.961 (.026)	-.089* (.059)
	Private veterinary services	.536 (.060)	.480 (.069)	.055 (.091)
Quality (1 if good and 0 otherwise)	Livestock extension services	.666 (.078)	.795 (.044)	-.128* (.090)
	Low-cost livestock feed	.871 (.053)	.826 (.052)	.044 (.074)
	Private veterinary services	.840 (.044)	.423 (.068)	.417*** (.081)

Notes: Values in brackets are the number of households that used the policy. Values in parentheses are standard errors. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

Finally, the households' assessment of quality is more positive in the South than in the North for livestock extension services, while it is more positive in the North for private veterinarian services. Assuming, for a moment, that these assessments can be generalized to households that have not had access to these policies, it could be said that these assessments (physical accessibility and cost of service) can influence households' decisions to use these services, just as they (quality of service) can have an impact on the outcome being measured. It would therefore be important to take this information into account in our estimates. Unfortunately, this information is too censored to be used directly in our estimates. However, including a dummy variable for the households' region of residence (North or South) in our estimation will allow us to incorporate part of this information.

C6 Evaluating the policy effects

We evaluate the effects of the three policies separately because each policy was originally intended to resolve a specific problem. Therefore, depending on its needs, a household can decide to access different policies at a different period of in time, or not at all. For example, a household can decide to access the private veterinary services during the dry and wet season, a season conducive to the development of livestock diseases. While, in the dry and hot season[3], it can decide to access the low-cost livestock feed program because of the scarcity of pastureland during this season. Therefore, before deciding to access the low-cost livestock feed program, the effect of private veterinary services may have already been observed due to the fact that the household had access to it. Also, in this model, the household's decision to access low-cost livestock feed is not dependent to its previous decision to access private veterinary services. Evaluating the simultaneous effects of the three policies may not be relevant in this setting because the survey does not provide any information on the precise time of the year when each household had access to a policy.

Moreover, as mentioned, household access to a policy may be independent from its access to another policy. Therefore, we prefer to assess the impact of each considered policy separately.

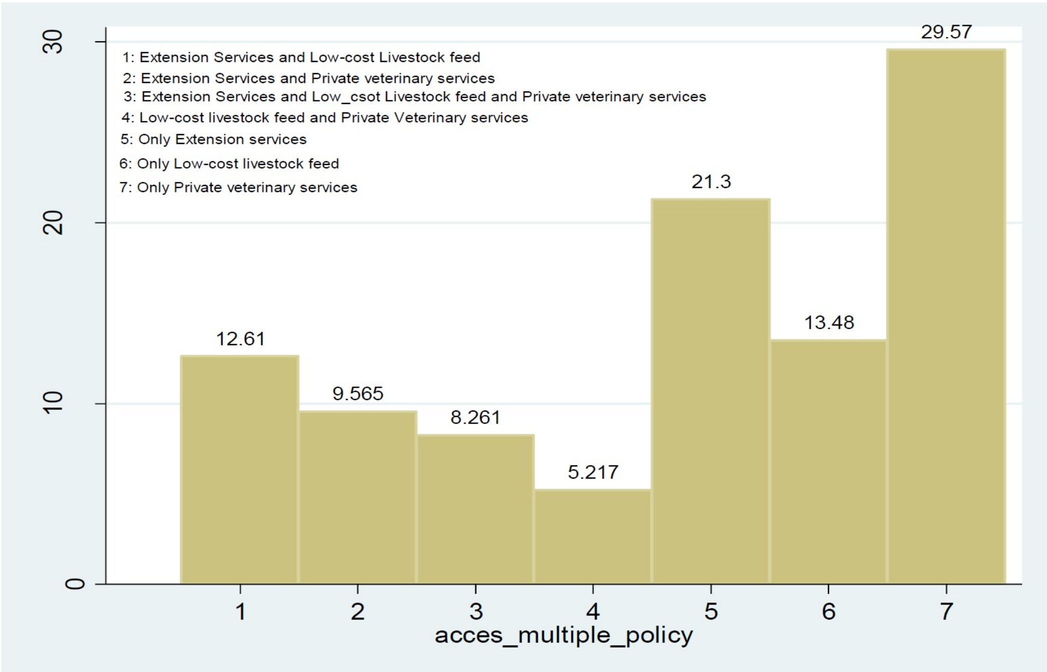


Figure C1: Distribution of households that have access to at least one policy among the three studied

[3]The dry and hot season corresponds to the period from February to May, while the dry and wet season corresponds to the period from October to January.

C7 Generalized boxplots of calorie intake

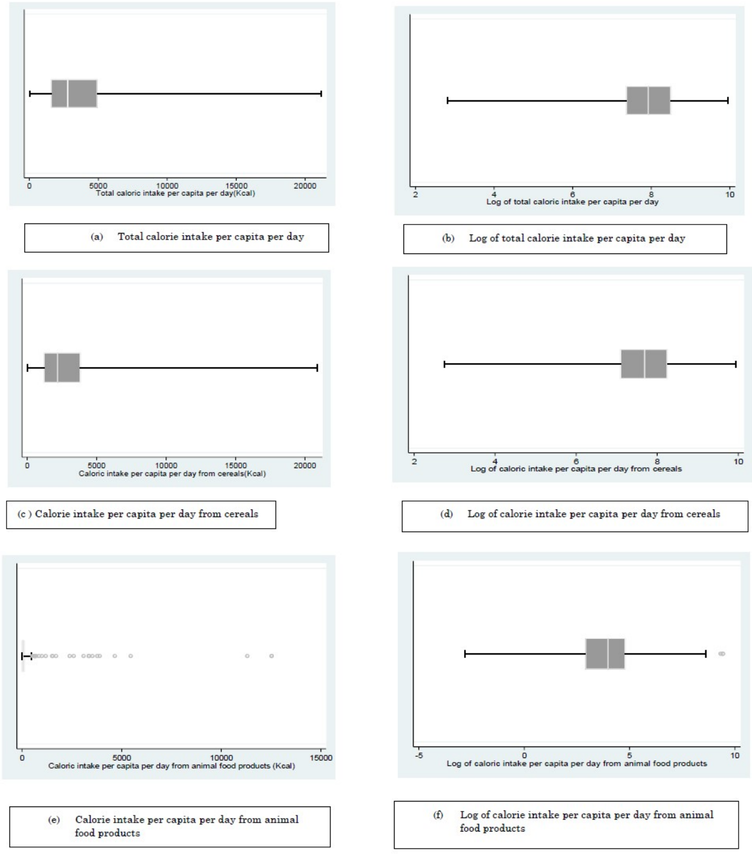


Figure C2: Generalized boxplots of calorie intake

C8 Comparison of the control group and the treated group on the basis of covariates used in the IPWRA model

Table C5: Baseline comparison

	Policies					
	Extension services		Low-cost livestock feed		Private veterinary services	
	Control	Treated	Control	Treated	Control	Treated
	(N=477)	(N=119)	(N=505)	(N=91)	(N=475)	(N=121)
Covariates for IPWRA (mean values)						
Sex of household head (1 if female)	.054 (.051)	.025 (.024)	.053 (.050)	.021 (.021)	.054 (.05)	.024 (.02)
Age of household head (in years)	44.92 (218.47)	44.14 (203.19)	44.40 (214.57)	46.78 (216.12)	44.97 (220.45)	43.95 (195.28)
Area of living (1 if in the South)	.58 (.24)	.69 (.21)	.61 (.24)	.57 (.25)	.648 (.22)	.43 (.25)
Proportion of children (0-3 years old)	.10 (.02)	.12 (.02)	.11 (.01)	.11 (.01)	.10 (.01)	.13 (.01)
Proportion of children (4-10 years old)	.25 (.03)	.27 (.02)	.25 (.03)	.29 (.03)	.25 (.03)	.29 (.03)
Proportion of youths (11-16 years old)	.10 (.01)	.12 (.02)	.11 (.01)	.11 (.01)	.10 (.01)	.12 (.02)
Proportion of young adults (17-20 years old)	.12 (.02)	.11 (.02)	.12 (.02)	.09 (.01)	.12 (.02)	.10 (.01)
Ethnic group						
- Tuareg (1 if yes and 0 otherwise)	.24 (.18)	.20 (.16)	.22 (.17)	.28 (.20)	.21 (.17)	.29 (.21)
- Fulani (1 if yes and 0 otherwise)	.53 (.25)	.62 (.24)	.55 (.25)	.56 (.25)	.60 (.24)	.35 (.23)
- Haussa (1 if yes and 0 otherwise)	.15 (.13)	.10 (.09)	.15 (.13)	.08 (.08)	.14 (.12)	.14 (.12)
Instruction level of household head						
- None (1 if yes and 0 otherwise)	.95 (.05)	.94 (.06)	.94 (.04)	.94 (.05)	.95 (.04)	.92 (.06)
- Primary (1 if yes and 0 otherwise)	.03 (.04)	.04 (.04)	.03 (.03)	.04 (.04)	.03 (.03)	.04 (.04)

Notes: Values in parentheses are variances

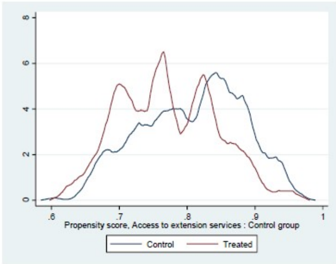
Table C6: Comparison after weighting with IPWRA

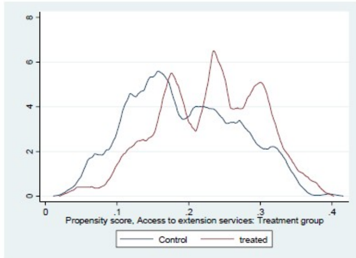
	Policies					
	Extension services		Low-cost livestock feed		Private veterinary services	
	Raw standardized difference	Weighted standardized difference	Raw standardized difference	Weighted standardized difference	Raw standardized difference	Weighted standardized difference
Covariates for IPWRA (mean values)						
Sex of household head (1 if female)	-.14 (.47)	.02 (1.11)	-.16 (.42)	-.04 (.81)	-.15 (.47)	-.09 (.62)
Age of household head (in years)	-.05 (.93)	-.01 (1.01)	.16 (1.00)	.01 (.94)	-.07 (.88)	.01 (.97)
Area of living (1 if in the South)	.24 (.87)	-.00 (1.00)	-.07 (1.03)	-.00 (1.00)	-.44 (1.08)	.11 (.93)
Proportion of children (0-3 years old)	.08 (1.07)	.01 (1.12)	.02 (1.08)	-.02 (1.08)	.24 (1.01)	-.08 (.85)
Proportion of children (4-10 years old)	.13 (.86)	.01 (.98)	.23 (.97)	.02 (1.01)	.21 (.81)	-.15 (.99)
Proportion of youths (11-16 years old)	.15 (1.26)	-.04 (1.16)	-.00 (1.06)	-.00 (1.00)	.16 (1.21)	-.04 (1.07)
Proportion of young adults (17-20 years old)	-.08 (1.03)	.00 (1.24)	-.21 (.64)	-.03 (.79)	-.12 (.62)	-.15 (.64)
Ethnic group						
- Tuareg (1 if yes and 0 otherwise)	-.09 (.88)	-.03 (.94)	.14 (1.18)	-.03 (.96)	.16 (1.20)	-.06 (.91)
- Fulani (1 if yes and 0 otherwise)	.18 (.95)	-.01 (1.00)	.02 (1.00)	.04 (.98)	-.52 (.95)	.08 (.97)
- Haussa (1 if yes and 0 otherwise)	-.15 (.71)	.05 (1.10)	-.19 (.63)	-.03 (.92)	-.00 (1.00)	-.02 (.94)
Instruction level of household head						
- None (1 if yes and 0 otherwise)	-.03 (1.16)	-.07 (1.31)	-.01 (1.07)	-.03 (1.13)	-.11 (1.56)	.06 (.75)
- Primary (1 if yes and 0 otherwise)	.02 (1.11)	.08 (1.41)	.03 (1.17)	.06 (1.33)	.01 (1.09)	-.06 (.70)

Notes: Values in parentheses are variances ratio

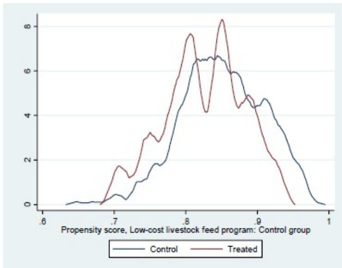
C9 Overlapping assumption

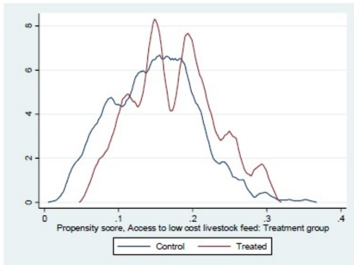
- **Propensity score overlap graph for Extension services**



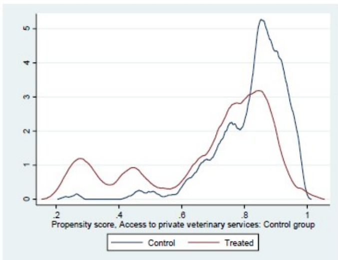


- **Propensity score overlap graph for Low-cost feed program**





- **Propensity score overlap graph for Private veterinary services**



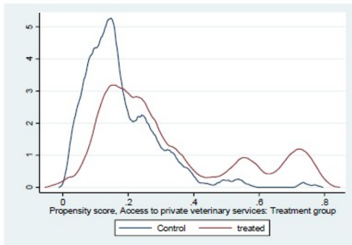


Figure C3: Overlapping assumption

Notes: This figure present for each of the three selected policies the propensity score overlap graph for both control and treatment group.

C10 Mediations models for private veterinary services and low-cost livestock feed

Table C7: Mediation model for private veterinary services

	Panel A: 2SLS/OLS			
	Outcomes			
	Log of household dietary diversity score	Log of total daily per capita calorie intake	Log of daily per capita calorie intake from cereals	Log of daily per capita calorie intake from animal food products(OLS)
Mediator				
Log of annual profit from livestock activities	0.423*** (.118) [0.279, 0.810]	-0.711** (.240) [-1.532, 0.359]	-0.939*** (.272) [-1.965, 0.597]	0.413*** (.111)
Policy				
Access to private veterinary services	0.06 (.050)	-0.081 (.158)	-0.121 (.172)	0.229 (.205)
	Panel B: First Stage			
	Mediator			
	Log of annual profit	**Log of annual profit**	**Log of annual profit**	**Log of annual profit**
Policy				
Access to private veterinary services	0.097 (.094)			
Instruments				
Pastoral season (1 if good)	0.32*** (.103)			
Annual maximal temperature in level	-19.375*** (6.154)			
Annual maximal temperature squared	0.275*** (.086)			
Control variables	**X**	**X**	**X**	**X**
Test of exogeneity of log profit (Robust F)	[0.00]	[0.00]	[0.00]	[0.99]
Test of over identifying restriction: Chi 2 test	[0.11]	[0.14]	[0.10]	-
F-statistic for first stage excluded instruments	9.04	9.04	9.04	-
Robust test for weak instruments: Effective F-statistic, MP test [Critical value at the 10 percent level]	13.46 [13.70]	13.46 [13.70]	13.46 [13.70]	-
R square	-	-	-	0.12
Number of observations	595	595	595	516

Notes: Values in brackets are critical p-values, and values in parentheses are robust standard errors. *, ** and *** indicate significant differences at the 10%, 5% and 1% levels, respectively. The robust test for weak instruments is proposed by Olea and Pflueger (2013) and computed using a Stata package made available by Pflueger and Wang (2015). MP: Olea Montiel and Pflueger. The confidence interval in brackets is the identification-robust LC_2sls 95 percent confidence interval for linear IV. These confidence intervals are computed using the package twostepweakiv proposed by Sun (2018). The distortion cutoff level obtained from this test is 14%, 9% and 10% for the model of dietary diversity score, total calories intake and calories intake from cereals, respectively, which does not exclude the possibility of a weak instrument The distortion cutoff level obtained from this test is 14%, 9% and 10% for the model of dietary diversity score, total calories intake and calories intake from cereals, respectively, which does not exclude the possibility of a weak instrument.

Table C8: Mediation model for low-cost feed

	Panel A: 2SLS/OLS			
	Outcomes			
	Log of household dietary diversity score	**Log of total daily per capita calorie intake**	**Log of daily per capita calorie intake from cereals**	**Log of daily per capita calorie intake from animal food products(OLS)**
Mediator				
Log of annual profit from livestock activities	0.418*** (.115) [0.279, 0.815]	-0.748 ** (.242) [-1.570, 0.396]	-0.985*** (.276) [-2.023, 0.586]	0.408*** (.110)
Policy				
Access to low-cost livestock feed	0.138** (0.057)	0.289* (.175)	0.339* (.200)	0.350* (.184)
	Panel B: First Stage			
	Mediator			
	Log of annual profit	**Log of annual profit**	**Log of annual profit**	**Log of annual profit**
Policy				
Access to low-cost livestock feed	0.175 (.125)			
Instruments				
Pastoral season (1 if good)	0.314*** (.087)			
Annual maximal temperature in level	-20.188*** (6.50)			
Annual maximal temperature squared	0.286*** (.090)			
Control variables	X	X	X	X
Test of exogeneity for log profit: Robust F	[0.00]	[0.00]	[0.00]	[0.97]
Test of over identifying restriction: Chi 2 test	[0.12]	[0.18]	[0.15]	-
F-statistic for first stage of excluded instruments	8.88	8.88	8.89	-
Robust test for weak instruments: Effective F-statistic, MP test [Critical value at the 10 percent level]	13.13 [13.92]	13.13 [13.92]	13.13 [13.92]	-
R square	-	-	-	0.13
Number of observations	595	595	595	516

Notes: Values in brackets are critical p-values, and values in parentheses are robust standard errors. *, ** and *** indicate significant differences at the 10%, 5% and 1% levels, respectively. The robust test for weak instruments is proposed by Olea and Pflueger (2013) and computed using a Stata package made available by Pflueger and Wang (2015). MP: Olea Montiel and Pflueger. The confidence interval in brackets is the identification-robust LC_2sls 95 percent confidence interval for linear IV. These confidence intervals are computed using the package twostepweakiv proposed by Sun (2018). The distortion cutoff level obtained from this test is 14%, 9% and 10% for the model of dietary diversity score, total calories intake and calories intake from cereals, respectively, which does not exclude the possibility of a weak instrument The distortion cutoff level obtained from this test is 14%, 9% and 10% for the model of dietary diversity score, total calories intake and calories intake from cereals, respectively, which does not exclude the possibility of a weak instrument.

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