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Poverty analysis in the lowlands of Papua New Guinea underscores climate vulnerability and need for income flexibility*

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A severe El Niño event in 2015/16 decimated an important share of Papua New Guinea's (PNG) local crop production, leaving 10 per cent of the population with significant food shortages. Lack of recent socio-economic data and analysis of the country's rural population impeded efforts to plan and mitigate the ensuing food crisis. This paper presents the most recent poverty analysis in Papua New Guinea in nearly a decade, and a renewed effort to inform rural production, consumption and livelihood patterns in some of the country's most remote, lowland areas. We designed a rural household survey that collected detailed consumption and expenditure data to explore poverty prevalence and correlates of per capita household expenditure. Results suggest that approximately half of the sampled individuals live in households with total per capita expenditures below the poverty line. Climate shocks have significant and possibly long-term consequences for household welfare. Households that experienced a drought in the last 5 years are associated with significantly lower per capita expenditures. Labour diversification, via migration, is associated with greater welfare. Households with at least one migrant member are associated with 13 per cent greater per capita expenditure.

Key words: climate vulnerability, consumption expenditure analysis, household survey, Papua New Guinea, poverty analysis.

1. Introduction

An estimated 800,000 people, or about 10 per cent of the PNG population, experienced severe food shortages in 2015/16 due to a severe El Niño-Southern Oscillation (ENSO) event (Kanua *et al*. 2016; Baynes *et al*. 2017). However, given the lack of recent, detailed data on local food systems, agriculture, economic trends, and household living standards in PNG, emergency relief was designed with a limited understanding of which

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locations most needed assistance and what form of assistance was required (Kanua *et al.* 2016). More frequent shocks linked to climate change and periodic ENSO events will continue to challenge agricultural livelihoods in PNG. These shocks combined with ill-informed development policy and assistance may significantly stall rural economic growth opportunities.

This analysis speaks to some of the wider development challenges experienced in other countries. Similar to many less-developed countries in Africa South of the Sahara and Southeast Asia, the population of PNG is predominantly rural, and the majority of the poor live in rural areas (Balisacan *et al.* 2003; Myint 2016; Arndt *et al.* 2016). The rural poor in PNG are often remote, and conducting robust analysis of poverty prevalence that includes these populations is challenging. This study includes analysis of very remote (over 10 hours travel time to any town) to relatively better-connected households and underscores the importance of income flexibility. While access to land remains an important asset of the rural poor, the ability to leave the land (via migration) is strongly associated with improved welfare outcomes, controlling for differing biophysical environments and capital (labour, land and financial) endowments. In addition, our analysis suggests that poverty rates remain high within the survey sample areas, highlighting the need to better understand areas where poverty remains intractable and households are vulnerable to adverse shocks. While Malawi, Ethiopia and Uganda experienced significant decreases in poverty rates over the last several decades, achievements in poverty reduction remain vulnerable to climate shocks (Dercon *et al.* 2012; Alexandre 2016; Mussa and Pauw, 2011; Baulch and Hoddinott 2000). PNG is no stranger to adverse shocks; the household data analysed in this paper reflect the livelihood strategies pursued in climate-vulnerable environments and underscore the need for cost-effective, appropriate safety net programs.

Only two household surveys suitable for nationally representative poverty measurements have been implemented in PNG; these were completed in 1995/96 and 2009/10, respectively (Gibson and Rozelle 1998; Gibson 2012).[1] However, a variety of work has tracked poverty prevalence and severity over time. Allen *et al.* (2005) and Bourke and Harwood (2009) describe production potentials of rural areas in PNG and draw linkages to the vulnerability of locations with poorer environmental conditions. Gibson *et al.* (2005) used the 2000 population census and 1996 PNG Household Survey data to predict poverty rates at a finer geographic scale. They find substantial spatial heterogeneity of poverty prevalence in PNG, with higher poverty rates in Sandaun province and along the mountain range of the highlands characterised by high elevation, cold climate, and risk of erosion. Location-specific studies continue to inform development challenges to reducing poverty in rural and urban areas of PNG. For example, Rogers *et al.* (2011) report that

[1] The 14-year gap between these surveys creates significant challenges in comparing poverty rates (Gibson 2012).

isolated villages in Obura-Wonenara district with poor access to markets and services, and low education levels face significant challenges to meeting basic daily living requirements. A more recent study in the Autonomous Region of Bougainville collected household livelihood data from over 2000 cocoa-farming households and reports that greater education levels are associated with higher-productivity and increased incomes, controlling for farm size and number of trees (Walton *et al.* 2020).

This paper contributes to the literature in several ways. First, it provides the first updated quantitative analysis of consumption expenditure levels in PNG in almost a decade using household survey data recently collected by the International Food Policy Research Institute (IFPRI). In doing so, we calculate consumption baskets specific to each survey area to calculate geographically unique poverty lines. This is particularly useful for countries like PNG, characterised by varying agro-ecological potential and capital endowments, which reflect important differences in consumption baskets, food prices and household welfare. Second, we evaluate the diversity and differences of food baskets in each survey area to identify potential shortfalls of protein consumption among sample households. Finally, we utilise the updated household expenditure values to isolate the correlates of poverty within the context of rural lowland PNG to inform potential entry points for policy planning and targeted investment.

The remainder of this paper is organised as follows. Section 2 provides an overview of the survey sample and a selection of descriptive statistics. Section 3 introduces the poverty analysis methodology used in the Poverty Line Estimation Analytical Software (PLEASe) package and describes the methodology employed to evaluate the correlates of poverty in the four survey sites in PNG. Section 4 discusses results of the poverty analysis, including information on site-specific food baskets and correlates of total consumption expenditure. Section 5 concludes by outlining potential policy measures to be further investigated.

2. PNG household survey on food systems

The PNG Household Survey on Food Systems was implemented in four rural, lowland areas of PNG – East Sepik (Maprik, Wosera-Gawi and Yangoro-Saussia districts), West Sepik (Nuku district), and Madang (Middle Ramu and Usino Bundi districts) provinces and the Autonomous Region of Bougainville (ARoB – Buin and Siwai area of Southern Bougainville) (Figure 1). A total of 1,026 households in 70 communities were surveyed (International Food Policy Research Institute 2019). While travelling to the proposed study areas prior to survey implementation, we observed little variability in production and food systems *within* visited communities, although differences were identified *between* visited communities. This lack of apparent variance within communities presented a challenge for planning a representative household survey that, by design, sampled households clustered at community level. Given the apparently low variance in key variables within communities, but greater variance across communities, the survey sample was designed to be as spatially extensive as possible (i.e. incorporating 70 communities) within the study areas.

The sample was split between communities that were beginning a World Vision (an international non-governmental organisation that provides development programs in PNG) development program and communities not receiving nor planning to receive the World Vision (WVI) intervention (Table 1). While both WVI and non-WVI communities were randomly selected from within their respective strata, some restrictions were necessary given that mobility in PNG is logistically difficult, potentially unsafe, and time consuming. This gives rise to two potential sources of sample selection bias that may affect overall data analysis. First, WVI did not randomly select communities for participation in their development programs, nor are their program communities geographically spread across the survey province. Beyond security concerns and transportation logistics that impede randomisation of program communities, WVI worked with the Cocoa Board of Papua New Guinea to select communities affected by the recent cocoa pod borer infestation in order to implement a project to provide cocoa pod

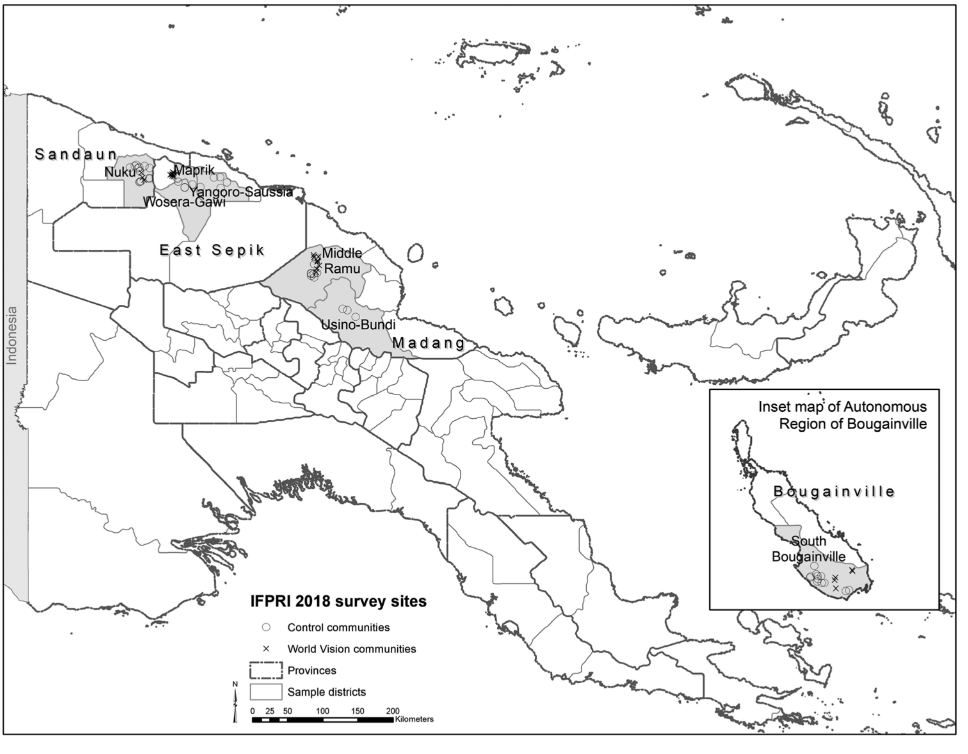

Figure 1 Community locations of the survey sample. Source: International Food Policy Research Institute (2019). *Note:* The boundaries and designations used on maps do not imply official endorsement or acceptance by the authors.

Table 1 Number of households surveyed by survey area and program community

	ARoB	East sepik	Madang	West sepik	Total sample
Non-World vision	181	125	168	193	667
World vision	70	120	124	45	359
Survey sample households	251	245	292	238	1,026
Sample households included in analysis	240	240	292	229	1,001

Source: International Food Policy Research Institute (2019).

borer-resistant cocoa tree seedlings to rural farmers. Thus, the survey sample that includes WVI communities may not capture varying characteristics representative of other communities outside of the WVI development portfolio.

Second, given security and travel considerations, the non-WVI communities eligible for inclusion were limited to those within 1 to 4 hours travel time of WVI program communities. The one-hour travel time restriction was imposed to avoid possible influence of nearby WVI programs on the non-WVI communities, which were identified using a GIS analysis that considered the location of roads and walking times across different terrain types. Within each community (both WVI and non-WVI communities), 15 households were randomly selected for enumeration.

The survey questionnaire collected a holistic set of indicators to evaluate rural livelihoods. Survey modules included questions about agricultural production, labour activities, consumption and expenditure, household assets, and economic shocks. For this analysis, we focus on survey data related to consumption and expenditure. After close evaluation of the data, 25 households were dropped from the original sample because there was incomplete information on consumption and expenditure in these households. The remainder of the paper is based on the sample as represented in Table 2, consisting of 1,001 households.[2]

We find that agricultural production is closely linked with overall food consumption in PNG. Approximately 73 per cent of the total food budget in surveyed households is own-produced (Table 2). However, differences exist between survey areas. For example, 86 per cent of the total food budget is derived from own-produced sources in remote households located in Middle Ramu, Madang district. Conversely, households in the relatively well-connected and more market-oriented Buin and Siwai districts in the ARoB sample depend more heavily on purchased items, with less than half of the food budget derived from own-production (Table 2).

Roots and tubers are the largest source of calories in most survey areas (Figure 2). In ARoB, grain consumption is dominant and primarily

[2] For more detail on the sampling strategy and questionnaire, see Schmidt *et al.* (2019).

Table 2 Primary source of food, by expenditure category (% of value of total food consumed)

	ARoB	East Sepik	Madang	West Sepik	Total sample
Purchased	46.6	27.5	10.5	27.0	24.6
Own-produced	48.8	70.5	86.2	70.8	72.5
Gift	2.4	1.7	3.0	1.6	2.2
Food away from home	2.2	0.4	0.3	0.5	0.7
Number of households	240	240	292	229	1,001

Source: International Food Policy Research Institute (2019).

comprised of packaged rice, owing to the importance of processed and marketed goods in the consumption basket. Sago (categorised amongst roots and tubers for this study), a starchy food extracted from the pith of the trunks of sago palm (*Metroxylon*), is particularly important in the mainland survey areas. Ninety per cent or more of households in East and West Sepik and Madang reported consuming sago in the past week. More than 60 and 57 per cent of survey households reported consuming sweet potato and yams, respectively.

Figure 2 also highlights the low level of protein consumption derived from animal-sourced foods across survey areas. Given that the survey did not collect body weight information of every individual in the household, we estimate the protein needs per household using adult male equivalents. The Recommended Dietary Allowance (RDA) for protein consumption is 0.8 grams per kilogram of body weight (Trumbo *et al*. 2002). Drawing from the Benjamin (2007) study that reported average adult weights in four areas of Papua New Guinea, we assume an average adult male weight of 58 kilograms, which corresponds to an RDA of 46 grams of protein per day. Following (Coates *et al*. 2017), we calculate the number of adult male

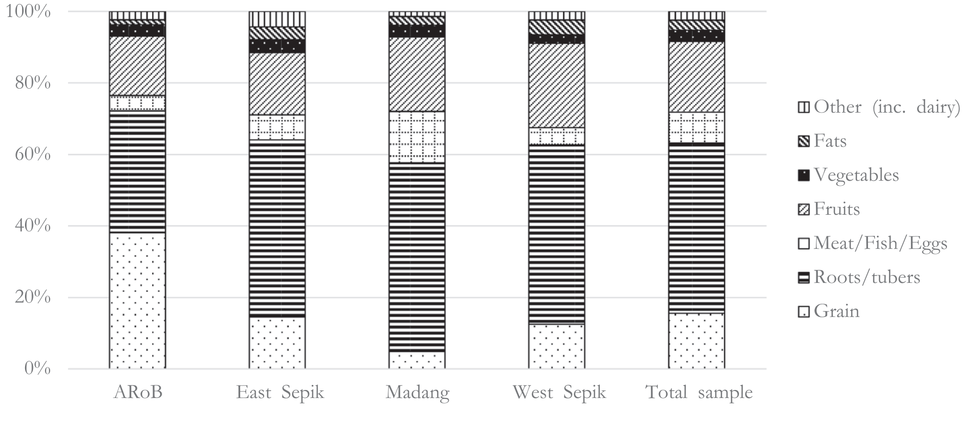

Figure 2 Share of calories consumed by food group and survey. Source: International Food Policy Research Institute (2019).

equivalents (AME) per household based on individuals' energy needs relative to an adult male. We then compare the total amount of reported protein consumed within the household to the estimated protein requirements based on the household AME. We find that almost half of the surveyed households do not have sufficient protein available. These results support earlier work that found protein deficiency widespread among rural households in PNG (Igua 2001; Mueller *et al.* 2001).

Comparing the composition of the food baskets of relatively poor households across survey areas highlights the need to calculate separate poverty lines for each area (Table 3).[3] For example, packaged rice represents nearly a quarter of food basket expenditure in ARoB, but does not appear in the Madang basket and appears in much smaller shares in East and West Sepik (8.5 and 6.1 percent, respectively). Similarly, sago comprises just under one-third of total food basket expenditure shares in all survey areas except ARoB (Table 3). Almost two-thirds of the food basket expenditure in the Madang survey area in Middle Ramu consists of starchy foods (sago, yam, banana, sweet potato and taro) and comprises 9 food items. In contrast, the East Sepik sample, which is located near Maprik town and produces vanilla for international markets, has a more diverse food basket with 15 food items.

3. Materials and methods

3.1 Poverty analysis

We quantify household welfare as the per capita daily value of total consumption expenditure, henceforth referred to as 'total expenditure'. Total expenditure includes the value of both non-food and food consumption and expenditure, where the latter includes the value of both purchased and non-purchased food consumption. We do not use household income as our measure of welfare for several reasons. First, rural incomes in PNG are difficult to quantify because most households are engaged in subsistence agriculture. Second, rural cash incomes vary throughout the year and may be difficult for respondents to recall. Finally, wages fluctuate due to seasonal variation in crop prices and demand for labour and other goods and services. Particularly in contexts like PNG, where subsistence food production is common and the informal economy accounts for a significant portion of economic activity, total expenditure provides a more reliable indicator of household welfare.

[3] We recalculate region-specific poverty lines (rather than update from previous studies) to account for differences in data collection methodologies across studies, non-uniform changes of food item prices and changes in consumption baskets over time.

Table 3 Poverty line food baskets based on expenditure shares among relatively poor households, by survey area

ARoB			East Sepik		
Packaged rice	24.3		Sago	30.5	
Sweet potato	16.5		Packaged rice	8.5	
Tinned fish	9.4		Bananas	8.1	
Bananas	8.5		Chinese taro	6.9	
Coconuts	6.4		Tinned fish	6.2	
Dark leafy greens	3.7		Coconuts	5.2	
Soft drink	3.6		Sweet potato	4.2	
Pasta/ 2 min. noodles	3.5		Dark leafy greens	3.8	
Other fish	3.1		Other meat	3.8	
Yam	3.1		Other fresh fruit	3.1	
Cassava	2.9		Taro	2.8	
Chinese Taro	2.8		Yam	2.7	
Packaged salt	2.6		Other fish	2.4	
Excluded foods†		9.5	Packaged vegetable oil	2.4	
			Excluded foods†		9.2
Total	90.5	9.5	Total	90.8	9.2

Madang			West Sepik		
Sago	29.1		Sago	30.9	
Yam	17.1		Coconuts	9.5	
Other fish	13.5		Yam	7.4	
Bananas	9.3		Bananas	6.5	
Coconuts	7.2		Dark leafy greens	6.1	
Dark leafy greens	5.4		Packaged rice	6.1	
Other fresh fruit	3.6		Tinned fish	5.9	
Sweet potato	3.5		Other meat	5.0	
Taro	2.7		Other fresh fruit	4.1	
Excluded foods†		8.6	Chinese taro	4.0	
			Packaged salt	3.5	
			Taro	3.4	
			Excluded foods†		7.6
Total	91.4	8.6	Total	92.4	7.6

Source: International Food Policy Research Institute (2019).
†Regional food baskets are based on the consumption patterns of relatively poor households. By including the most important food items (i.e. those which account for approximately 90 per cent of food expenditures), the basket is restricted to foods which are consumed by a larger share of poor households. The assumption is that (approximately) 10 per cent of the remaining expenditures are comprised of a more disparate number of food items consumed by a smaller number of households.

To determine the value of total expenditure, the following data were collected for each sample household:

1. Weekly food consumption expenditures – including the value of food eaten by all members of the household over the past week
2. Regular monthly expenditures – including non-food items such as firewood, soap, cigarettes, betel nut, and other everyday items needed in the home.
3. Annual expenditures – including larger non-food items and services – for example, clothing, furniture and utilities.

The survey asked respondents to report the quantity of each food item that the household consumed during the previous week; its source (own-produced, purchased, or received as a gift); and the amount paid for purchased items.[4] In doing so, survey respondents were provided picture aids of food items and their sizes for those items commonly sold in bunches, heaps, or non-metric units. For example, sweet potatoes can be sold in small, medium or large heaps; thus, the respondent was shown three heap size options they could use as a reference size to report their own households' consumption during the previous seven days. Foods were weighed, during survey preparation, by their reference sizes displayed in the picture aids to convert heaps (or other unconventional measurements such as bags, bunches, and single items) to kilogram equivalents.[5]

We assign food acquired by own-production or gifts the median reported household purchase price of the item within the survey community or study area.[6] Food consumption expenditures are calculated accounting for the reported quantity of each food that the household consumed. For meals and foods eaten outside the home, households were asked to report total expenditures. For monthly and annual non-food expenditures, respondents were asked to report the total household value of each good or service. We follow Deaton and Zaidi (2002) when constructing the non-food expenditure aggregates, whereby 'lumpy' expenditures such as marriages, burials, and other infrequent purchases are excluded from the aggregate calculation. Similarly, loan payments, bank charges, or fees which are considered deductions from income are not included in the consumption aggregate. Expenditures on items such as petrol, public motorised vehicle (PMV) transportation costs, clothing, furniture, and school fees are included in the total expenditure aggregate. The sum of food consumption expenditure and non-food expenditure yields total expenditure, which includes the value of non-purchased foods. All expenditures are adjusted for the length of the recall period and for the number of household members, so total expenditure is expressed in daily per capita terms.

We use the Poverty Line Estimation Analytical Software (PLEASe) program to compute cost of basic needs poverty lines and estimate the

[4] Bounded recall, in which survey participants are visited twice during the survey period to better frame recall response, was not employed due to survey budget constraints.

[5] The published household questionnaire and survey data provides a comprehensive list of unconventional measurements used in the survey (International Food Policy Research Institute, 2019).

[6] Prices were assigned at the most local level for which there are at least ten price observations, with community as the most disaggregated level. Consumption expenditures are not estimated for own-produced or gifted food items for which there are fewer than five reported prices in the total sample. Appendix Table I reports the number and share of price observations that are derived at each geographic level within the survey.

percentage of individuals who live in poor households (Arndt and Mahrt 2017).[7] Cost of basic needs poverty lines are designed to represent a minimum standard of living. More specifically, this minimum standard of living is defined by the cost of a basket of foods consumed by relatively poor households, adjusted to satisfy caloric needs, plus a non-food allowance based on non-food expenditure patterns of poor households (Ravallion 1994, 1998; Ravallion and Sen 1996; Wodon 1997). The cost of basic needs in developing country contexts is a true minimum standard of living and is largely comprised of food goods.[8] All household members are considered to be non-poor if the household has sufficient total expenditure to attain the reference utility level defined by the poverty line.

3.1.1 Utility-consistent poverty line estimation

Given that the household survey sample is comprised of households that are located in significantly different geographic and agro-ecological areas, variations in food availability and preferences are expected. Ravallion (2016) and Tarp *et al.* (2002) note that variations in relative prices across space and over time present a significant challenge to establishing a single basket of goods to ensure consistent and comparable utility for poverty analysis. Assuming substitutability among goods, the food basket must account for differences in local consumption patterns that respond to availability and price differentials over space and time (Ravallion 1994). However, defining regional food baskets forfeits the guarantee that poverty lines represent the same utility level, a condition guaranteed by a single national basket. As a result, households with the same real expenditure levels could be deemed poor in regions with more costly baskets that represent higher utility, while being deemed non-poor in regions with less costly, lower utility baskets. This inconsistency renders poverty rates incomparable.

Revealed preference theory provides a method for testing whether regional food poverty lines are utility-consistent (Gibson and Rozelle 2003; Ravallion and Lokshin 2006). Arndt and Simler (2005, 2007, 2010) developed an information theory approach for resolving utility inconsistency by imposing revealed preference constraints. Using the cross-entropy criterion, they minimise the directed distance between food quantities in original food baskets and estimated quantities that satisfy revealed preference conditions while also meeting the caloric target.

We estimate regional, utility-consistent poverty lines for each of the four survey areas. Regional poverty lines are determined by the consumption patterns of poor households, which are initially identified as those with per capita daily total expenditure in a bottom percentile corresponding to an

[7] Another approach to estimating a poverty line is the food energy intake calculation (Greer and Thorbecke 1986), however the cost of basic needs approach has become a more common benchmark over time.

[8] Arndt *et al.* (2017) provide a detailed explanation of the calculation of absolute poverty lines based on the cost of basic needs method including influencing factors and limitations.

assumed poverty rate. An iterative procedure is employed whereby the poverty rate is updated in each iteration and poor households are reselected until the poverty rate converges.

Food poverty lines are estimated to be the cost of meeting per capita calorie requirements based on food consumption expenditure shares and food prices of poor households. We consider the basket of food items in the top 90 per cent of food consumption expenditure shares of poor households in each area. The bottom 10 per cent of food consumption expenditure often consists of atypical foods that are eaten by a relatively small number of households and are thus trimmed from the basket (Arndt and Mahrt 2017). Regional food baskets are scaled to attain the regional average per capita minimum calorie requirement (assuming that individuals are moderately active). The food poverty line is then the per capita daily cost of acquiring the regional food basket based on quantity-weighted average regional prices reported by poor households. Finally, the food poverty line is rescaled to reflect 100 per cent of food consumption expenditure.

The regional non-food poverty line is the weighted average of per capita daily non-food expenditure of households with per capita daily total expenditure within 20 per cent of the food poverty line (Arndt and Mahrt 2017). The total poverty line is the sum of the food and non-food poverty lines in each region. The iterative procedure is implemented to ensure that poverty lines reflect the consumption patterns of actual poor households where poverty rates are updated in each iteration. After the final iteration, food baskets are entropy-adjusted, as necessary, to enforce revealed preference constraints, which ensures utility-consistent food poverty lines.

3.2 Correlates of total expenditure

Efforts to reduce poverty or foster local economic growth via government policy or international development assistance are often designed around household and community characteristics that are associated with household welfare. Identifying factors associated with household welfare can assist the design of specific investments to further improve development objectives. We model the correlates of per capita total expenditure based on an ordinary least squares (OLS) regression. Logged per capita daily total expenditure (our dependent variable) is adjusted by a spatial price deflator in order to take into account differences in the cost-of-living in the different survey areas of PNG. The spatial price deflator is an index calculated by taking the normalised ratio of each regional poverty line to a base regional poverty line (we use ARoB as the base poverty line). This is modelled as follows:

$$ln(Y_i) = \beta x_i + \varepsilon_i \quad (1)$$

where Y_i is the spatially adjusted total annual per capita consumption expenditure of household i in Papua New Guinea kina (PGK), x_i is a vector of household and community-level characteristics and ε_i is a random error term.[9]

A key concern when selecting potential influencing factors on overall welfare is exogeneity. Given that we are attempting to identify variables that are related to overall poverty levels, variables that are affected by current consumption in the household are excluded from the model (Haughton and Khandker 2009; Mukherjee and Benson 2003; Datt et al. 2000). Included in the model are household-level demographic, education, and employment structure variables. In addition, we use community fixed effects to consider important factors such as cell phone coverage, as well as local cultural and societal norms that may influence overall economic opportunities within the community. Finally, we cluster the standard errors to account for the multi-stage sampling design implemented in the household survey. The following section provides a detailed discussion of the poverty line analysis followed by an evaluation of the correlates of total household expenditures.

4. Results

4.1 Poverty analysis results

Considering area-specific food baskets and prices, we calculate regional utility-consistent poverty lines for each of the four survey areas. Individuals in households with per capita daily total expenditure below the total poverty line are considered poor. Following these definitions, approximately 50 per cent of individuals in the sample are living below the poverty line (Table 4). When taking into account differences in consumption preferences and prices, there are minimal differences in the poverty headcount across survey areas. Approximately 54 per cent of individuals live in poor households in West Sepik, followed by slightly lower rates in ARoB and East Sepik (52 and 51 percent). In Madang, an estimated 45 per cent of individuals live in poor households.

Although absolute poverty lines provide a threshold value to facilitate a categorisation of poor versus non-poor households, it may not capture a large share of the sample that is struggling to meet basic needs. For example, households with daily per capita expenditure valued at 10 toea (0.1 kina) above the poverty line and categorised as non-poor would still face many of the same challenges that a household with expenditure valued at 10 toea below the poverty line and categorised as poor. If poverty lines were 10 per cent higher, the percentage of individuals in the sample considered poor would increase by 6 percentage points to 56.1 per cent (Table 5). In the case of the Madang sample, the share of poor increases by nearly 8 percentage points (from 45.2 to 52.9 per cent) if the poverty line is increased by 10 per cent.

[9] The logarithm of per capita daily total expenditure is used as the dependent variable because its distribution more closely approximates the normal distribution than does the distribution of expenditure.

Table 4 Poverty headcount and utility-consistent absolute poverty lines (kina/capita/day)

	ARoB	East Sepik	Madang	West Sepik	Total Sample
Poverty headcount, per cent	52.1	50.7	45.2	54.6	50.2
Food poverty line	3.09	3.57	3.48	3.56	
Non-food poverty line	0.78	0.83	0.53	0.74	
Total poverty line	3.87	4.40	4.01	4.30	4.14†

Note: Poverty headcounts are based on the entropy-adjusted utility-consistent poverty lines and have been weighted by household size, so represent the share of the sample of each study area that is poor. These figures are not nationally representative. USD 1.00 = PGK 3.28 in June 2018.
Source: International Food Policy Research Institute (2019).
†4.14 PGK is the spatially adjusted poverty line estimated to provide an overall poverty headcount for the entire survey sample.

Table 5 Sensitivity of poverty headcount to changes in poverty line, per cent of individuals

	ARoB	East Sepik	Madang	West Sepik	Total Sample
Poverty line	52.1	50.7	45.2	54.6	50.2
Poverty line + 10%	58.8	54.5	52.9	58.6	56.1
Poverty line −10%	44.6	45.0	38.9	48.7	44.1

Note: The spatially adjusted poverty line is set at 4.14 kina per person per day after accounting for regional differences in food baskets and prices.
Source: International Food Policy Research Institute (2019).

Comparing the results presented here with earlier poverty assessments suggests that the poverty rate within the rural Momase region (where 3/4 of the household data were collected in the IFPRI survey sample) has changed very little since the last Household Income Expenditure Survey (HIES) in 2009/2010. However, such comparisons should be made with caution. The IFPRI survey focused on 4 geographically clustered areas that were not sampled to represent region level data. In addition, the survey methodology used in the IFPRI survey was based on household recall of food consumption, rather than a dietary diary employed in the 2009/10 HIES where consumption was calculated as a residual of food stocks and purchases.

Table 6 reports average values of covariates used in the OLS disaggregated by poor and non-poor households. On average, poor households have more household members and less formal education. Poor households also own less agricultural land. It is important to note, however, that land is not measured in hectares in many rural areas in PNG. Thus, the best option for evaluating land holdings would be to physically measure (via GPS or traditional compass-and-rope methods) each reported household agricultural plot. However, this method is time-consuming and costly, especially in PNG where gardens can be dispersed across multiple locations. Thus, pre-survey scoping visits sought to identify the second-best option for estimating land size, which resulted in the household head (or most knowledgeable person) being asked to estimate each garden size according to relative sport field sizes, which were then converted to hectares.[10,11] Similarly, we recognise that this estimation does not capture communal land use for animal grazing. However, very few households reported ownership of grazing livestock (only 6 and 2 households reported owning cows and goats, respectively). A greater share of households owned pigs (22 per cent), however scoping visits suggested that pigs are kept in private fenced enclosures in the survey areas.

The survey asked each household whether they had experienced a list of potential shocks during the last 5 years. Included in the list of shocks were questions about whether a household experienced a flood (or associated landslides) or drought (including irregular rains), respectively. Table 6 shows that a similar share of households within each expenditure category reported that they experienced a flood. However, a significantly larger share of poor households reported experiencing a drought (73 per cent) compared to non-poor households (63 per cent) during the last 5 years.

4.2 Correlates of per capita total expenditure results

Table 7 reports the results from the OLS regression examining the correlates of per capita daily total expenditure. We provide both the OLS coefficient estimate (column 1), and the interpretation of coefficients (per cent effect) for the log transformed dependent variable (column 2). Results reflect the rural focus of the survey whereby an extra hectare of owned land is associated with a 4 per cent increase in per capita daily expenditure. In addition, given that land markets are thin in PNG, and access to land is predominantly via inheritance, we also include a variable identifying whether the household head had a parent that was born in the village. Results suggest a quantitatively large positive association at more than 10 per cent with parental lineage being from the same community, with statistical significance at the 10 per cent level.[12]

Diversifying income sources is another means of potentially increasing overall welfare, and can also be used as a risk mitigation strategy among rural

[10] Overfifield (1998) highlights how perceptions of land holding size, ownership, and management can differ based on the sex of the survey respondent. For example, females may be offered usufruct rights to her husband's land (in a patrilineal community), whereby women may make independent decisions on crops planted, crop area utilized, and inputs used. This may lead to differing responses in estimated land ownership between males and females of the same household. The survey data used here asked only one household member to estimate household land ownership (by garden plot) utilized by any member of the household. This method would not capture gender nuances in reported household land ownership.

[11] Appendix Table II provides the non-metric unit to hectare conversions utilized to estimate plot size.

[12] Access to land for households without parental lineage is predominantly through marriage given the customary land tenure laws in PNG. Survey data suggest that almost two-thirds of the household heads that reported no parental lineage within the village entered the household through marriage. The second largest share of household heads (approximately 17 percent) came to the village to establish a household, while remaining heads came for a variety of other reasons including entering with a parent, to be near to a school or with relatives, etc.

Table 6 Differences in household characteristics between poor and non-poor

	All households	Poor households	Non-poor households	T-test
Daily expenditure per capita (PGK)	5.45	2.68	7.77	***
	(3.80)	(0.84)	(3.77)	
Age of household head, years	42.17	43.08	41.40	**
	(11.77)	(11.66)	(11.81)	
Male household head, 0/1	0.90	0.89	0.91	
	(0.30)	(0.31)	(0.29)	
Household size, number	5.89	6.49	5.38	***
	(2.22)	(2.18)	(2.12)	
Adult males in household	2.34	2.54	2.18	***
(age 15–64), number	(1.52)	01.59)	(1.43)	
Adult females in household	2.24	2.53	2.00	***
(age 15–64), number	(1.31)	(1.32)	(1.26)	
Household has 1 + migrants, 0/1	0.29	0.27	0.31	
	(0.45)	(0.44)	(0.46)	
Household head's parent born	0.77	0.78	0.76	
in village, 0/1	(0.42)	(0.41)	(0.43)	
Land area owned and	4.26	3.84	4.60	***
cultivated, hectares	(3.83)	(3.74)	(3.87)	
Max. years of education completed	8.78	8.37	9.13	***
by any household member	(3.06)	(2.92)	(3.14)	
Euclidean distance to major	55.32	53.69	56.68	
market towns (km)†	(49.30)	(48.66)	(49.83)	
Lives in community with	0.64	0.64	0.64	
reliable mobile phone network service	(0.48)	(0.48)	(0.48)	
Household experienced drought	0.68	0.73	0.63	***
in past 5 years, 0/1	(0.47)	(0.45)	(0.48)	
Household experienced	0.84	0.83	0.85	
flood/landslide in past 5 years, 0/1	(0.37)	(0.38)	(0.36)	
Average (30 year) total	2,706	2,664	2,741	
annual rainfall, mm	(937)	(902)	(964)	
Elevation, meters	155.52	158.86	152.72	
	(130)	(131)	(129)	
Number of households	1,001	456	545	

Note: Standard deviations are presented in parentheses below means; *t*-test *P*-value is derived from a t-test of equal variances for all variables except daily per capita expenditure and migrant dummy variable, which had unequal variances.
PGK = Papua New Guinea Kina.
Source: International Food Policy Research Institute (2019).
$^{***}P < 0.01$, $^{**}P < 0.05$, $^{*}P < 0.10$.
†Major market towns for each area include the following: Wewak (East Sepik), Maprik (East Sepik), Nuku (West Sepik), Vanimo (West Sepik), Madang (Madang), Kieta (Bougainville), Arawa (Bougainville) and Buka (Bougainville).

households that are heavily dependent on subsistence agriculture. Regression results suggest that labour diversification out of agriculture, measured by whether a household has a migrant member, has a significant positive association with per capita total expenditure. A household that reported at least one migrant that left the household (either permanently or temporarily) is correlated with 13 per cent greater per capita total expenditure relative to a household that reported no migrant household members.

Household level characteristics such as household size, sex of household head, and educational attainment follow previous studies with direction and significance as expected (Gibson 1999; Lanjouw and Ravallion 1995; Gounder 2013; Hall 2018). Each additional year of education completed is associated with a 4.2 per cent increase in per capita daily expenditure. Increases in educational attainment may be related to greater opportunities to seek off-farm employment. However, given that this is a cross-sectional study, we are unable to assign a direction of causation, that is, whether greater education drives increases in income or whether greater income drives households to invest more in education.

Papua New Guinea is susceptible to climate shocks. Regression results suggest that households that experienced a drought at least once in the last five years are associated with 16 per cent lower per capita expenditure compared to households that did not experience a drought (Table 7). However, a word of caution is merited to interpreting this correlation given that a household-specific shock variable may be correlated with unobserved factors such as level of risk aversion, reflecting a perception of risk rather

Table 7 Correlates of the log of total household expenditure

	Estimate	% effect	SE	P
Age of household head, years	−0.004	−0.4	0.011	0.754
Age of the household head (squared)	0.000	0.0	0.000	0.915
Male household head, 0/1	0.147	15.8	0.062	0.020
Household size, number	−0.123	−11.6	0.023	0.000
Adult males in household (age 15–64), number	0.022	2.2	0.026	0.398
Adult females in household (age 15–64), number	0.016	1.6	0.027	0.552
Household has 1 + migrants, 0/1	0.120	12.7	0.046	0.010
Household head's parent born in village, 0/1	0.096	10.1	0.054	0.080
Land area owned and cultivated, hectares	0.051	5.2	0.014	0.000
Land area owned and cultivated, hectares (sq)	−0.001	−0.1	0.001	0.127
Max. years of education completed by any household member	0.041	4.2	0.007	0.000
Household experienced drought in past 5 years, 0/1	−0.174	−16.0	0.045	0.000
Household experienced flood/landslide in past 5 years, 0/1	0.083	8.7	0.063	0.191
Average (30 year) total annual rainfall, mm	0.000	0.0	0.000	0.827
Elevation, meters	0.000	0.0	0.001	0.749
Euclidean distance to major market towns (km)†	−0.015	−1.5	0.017	0.393
Constant	1.952	–	1.131	0.089
Community level fixed effects	YES			
Observations	1,001			
R-squared	0.307			

Note: SE = Standard error, clustered at the community level. The per cent effect of a log-linear regression is evaluated by transforming the OLS coefficient: 100*(exp(β)-1). The effect of variables for which the squared term is also included in the regression is calculated as: $\beta_1 + 2\beta_2 {-} x$, where β_1 is the coefficient on the linear term, β_2 is the coefficient on the squared term, and $-x$ is the mean of the variable in question.
Source: International Food Policy Research Institute (2019).
†Major market towns for each area include the following: Wewak (East Sepik), Maprik (East Sepik), Nuku (West Sepik), Vanimo (West Sepik), Madang (Madang), Kieta (Bougainville), Arawa (Bougainville) and Buka (Bougainville).

than an objective measure of the shock itself. Community fixed effects could control for a climate shock variable; however, the data suggest large within-community variation of drought or flood exposure whereby 25–100 per cent of households within a community (with the greatest frequency of observations between 50–70 per cent) reported experiencing a drought.

Further evaluation of the household locations in this study suggests plausible variation in reported household experience of drought within the community. For example, while some households in the Middle Ramu survey area were located on the Ramu river, others were more than one kilometre (straight-line distance) from the river, which would make access to water during times of stress more difficult. In addition, during survey scoping visits in East and West Sepik, topographic characteristics such as hillside slope varied substantially within a community. These biophysical differences could alter water absorption on agricultural plots. Given that a variety of factors may be associated with the intra-community variation of reported drought, the influence of experiencing a drought on per capita expenditure should be interpreted with some caution.

A broad literature has investigated the relationship between distance to market and poverty reduction, including Gibson and Rozelle (2003), who report significant and positive effects of improved market access on total per capita expenditure in PNG. We include the straight-line distance from the household to the nearest major town in the analysis. Although the coefficient is negative, we do not find a statistically significant relationship with total expenditure. Given the clustered nature of the survey sample, this is not a surprising outcome as the distance to market variable is highly correlated with the community level fixed effects. However, recent analysis using household survey data and corresponding, detailed road maps of PNG in 1996 and 2010 show that investments in road infrastructure had strong positive effects on household welfare (Wiegand et al. 2017).

This analysis provides a snapshot of total expenditure at the time of survey implementation. Given the limited data and differing methodologies and survey instruments collected on consumption and expenditure in PNG over time, repeated cross-section or panel-level data analysis is not possible. Thus, results from this analysis are discussed in terms of correlates and partial effects, considering that certain bias (i.e. omitted variable bias and unwarranted endogeneity) may be introduced into the cross-section interpretation. Finally, the survey sample design used for this study used a clustered sampling approach, which is more cost-effective, especially in countries with limited infrastructure and high transportation costs (as is the case in PNG); however, a clustered sample can reduce estimate precision. For example, the standard errors on the terms whether a household has a migrant, land ownership in hectares, and household experience of drought are 10, 17, and 5 per cent larger when community-level clustering is accounted for relative to robust standard errors, respectively. However, these greater standard errors do not substantially affect significance levels in this specific study.

5. Conclusion

Although Papua New Guinea has benefited from increasing exports of natural gas and other natural resources, a large share of the rural population is unable to tap into these resources. The rugged terrain, extreme climate, and limited transportation infrastructure has left much of the rural population, comprising 89 per cent of the total population, with limited opportunities to take advantage of PNG's economic resources. In addition, very limited data collection and analysis in PNG has restricted more informed public investment and development assistance for economic growth and poverty reduction within the country, especially in rural areas.

Using the consumption and expenditure data collected in a recent rural household survey, this paper calculates utility-consistent and spatially explicit poverty lines to evaluate poverty levels of rural households in lowland areas of PNG. Overall, the poverty analysis finds that about half of the individuals in the sample live in households with expenditure levels below regional poverty lines.

We regress logged per capita total expenditure on a variety of factors hypothesised to influence overall economic well-being. Climate shocks (most recently from a severe El Niño event in 2015/16) had significant effects on agricultural productivity and overall household welfare in rural areas. Households that reported experiencing a drought in the last 5 years are associated with a 16 per cent lower per capita total expenditure. Given PNG's vulnerability to climate shocks, coupled with limited infrastructure that leaves remote communities with little recourse if a disaster strikes, investing in a productive safety net program may provide the needed assistance to maintain livelihood structures in rural areas during crisis.

In addition, increasing education, both within the agriculture sector (via agricultural extension, and agricultural training in primary schools) and outside of agriculture could support improved welfare outcomes. Similarly, bolstering off-farm labour and migration opportunities may help diversify risk from adverse climate shocks. Our analysis suggests that a household that reports having a member that has migrated (regardless of the reason for migration) is associated with significantly greater per capita total expenditure.

This analysis provides a snapshot of poverty levels and associated relationships to household characteristics. Previous work has pointed out that poverty is dynamic. Individuals move in and out of poverty based on seasonal effects, climate shocks, and economic changes over time (Baulch and Hoddinott 2000; Dang et al. 2011). Assuming more routine and comparable data collection occurs in PNG, panel datasets and repeated cross-sections would allow an examination of poverty over time. This would afford a greater understanding of which households remain poor over time and what factors contribute to households finding themselves in poverty traps. Panel data would allow further investigation of the magnitude of adverse shocks and impact of development programs and policy interventions on overall welfare across different geographical areas within the country.

Data availability statement

The data that support the findings of this study are openly available in Harvard Dataverse at https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/ZXRD6N, reference number V1.

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Appendix I

Table I Sources of food prices at various geographic levels

Price source	Food items (N)†	of N
Purchased unit price	4,798	36.25
Community price	80	0.60
Province price	1,678	12.68
Mainland price‡	1,485	11.22
Full sample price	4,363	32.97
No price available§	831	6.28
Total	13,235	100.00

Source: International Food Policy Research Institute (2019).
†Respondents were asked whether anyone in their household consumed a list of 40 food items in the past seven days. On average, households reported eating approximately 13 different food items out of the 40-item food list. This table does not include observations where households reported no consumption of a specific food item.
‡Mainland price is comprised of responses from West and East Sepik and Madang survey sites.
§Food items purchased fewer than five times across the full sample were considered to have insufficient price information.

Appendix II

Table II Land unit conversion factors

Non-metric reference unit in survey	Hectare conversions
Less than half volleyball court	0.0054
Half volleyball court	0.0081
Volleyball court	0.0162
Half soccer field	0.82
Soccer field	1.64

Source: International Food Policy Research Institute (2019).