Impacts of COVID-19 induced income and rice price shocks on household welfare in Papua New Guinea: Household model estimates

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Abstract
Concerns over the potential effects of the COVID-19 pandemic have led to trade restrictions by major rice exporters, contributing to an average 25% increase in Thai and Vietnamese rice export prices between December 2019 and March–September 2020. This article assesses the consequences of these rice price increases in Papua New Guinea (PNG), where 99% of rice is imported. Utilizing data from a PNG 2018 rural household survey along with earlier national household survey data, we examine rice consumption patterns in PNG and estimate demand parameters for urban and rural households. Model simulations indicate that a 25% rise in the world price of rice would reduce total rice consumption in PNG by 14% and reduce rice consumption of the poor (bottom 40% of total household expenditure distribution) by 15%. Including the effects of a possible 12% decrease in household incomes because of the COVID-19 related economic slowdown, rice consumption of the urban and rural poor fall by 20% and 17%, respectively. Maintaining functioning domestic supply chains of key staple goods is critical to mitigating the effects of global rice price increases, allowing urban households to increase their consumption of locally produced staples.

KEYWORDS
COVID-19, household welfare, multi-market model, Papua New Guinea, rice trade

JEL CLASSIFICATION
E17, F17, E21

1 INTRODUCTION
In response to the recent COVID-19 outbreak, several major rice exporting countries implemented policies to ensure adequate domestic supply. Vietnam suspended new contracts for rice exports for the month of April 2020. In India, mobility and logistics challenges due to social distancing regulations reduced availability of rice on the country’s domestic market and contributed to lower export volumes. As during the world price shocks of 2007 and 2008, rice export prices rose sharply, increasing by 25% for A1 Super in Thailand, and by 30% for 5% broken in Vietnam between December 2019 and May 2020, threatening the food security of countries dependent on rice imports. Although rice export restrictions eased and quarantine measures were loosened across the globe, Thai and Vietnamese rice prices remained relatively high in the subsequent months and were on average 22% and 28% higher, respectively, from March through September compared to December 2019.
Previous research examining Vietnam and India’s export bans during 2007/08 suggest that reserving production for domestic consumption did not protect local consumers from rice price inflation in Vietnam and India (Slayton, 2009). Panic buying in Indonesia spread to Vietnam, doubling rice prices in Ho Chi Minh City markets in March 2007, despite Vietnam’s export ban (Slayton, 2009; Timmer, 2009). The world price shocks had medium- and long-term policy effects, inducing rice importing countries to seek rice self-sufficiency by investing in domestic rice production, contributing to a long-term trend of rice price decline relative to other staple foods (Timmer, 2009). Although domestic rice production accounts for less than 1% of supply, Papua New Guinea (PNG) has followed similar policies, promoting domestic rice production even though large-scale production and processing are not competitive (PNG Department of Agriculture & Livestock, 2015; Gibson, 2001).

Nonetheless, PNG may be among the countries most affected by this recent rice price shock. Although the country has invested in attaining rice self-sufficiency, economic incentives for increasing domestic production remain weak. The lack of comparative advantage in producing rice, including the falling terms of trade relative to more valuable cash export tree crops, to a large extent explains why PNG has had little success in expanding domestic rice production (McKillop et al., 2009). Since 2005, rice imports have almost doubled from only 167 thousand tons/year to an estimated 300 thousand tons/year today (Schmidt and Fang, 2020). Rice imports made up the largest share (15%) of overall value of agri-food imports; however, rice imports comprised only about 3% of the total value of imports, on average, between 2014 and 2018 (BACI trade database; Gaulier & Zignago, 2010). Domestic policies to ensure that caloric needs are met during rice price shocks are important to avoid significant declines in overall food consumption.

Even though PNG’s domestic food economy is dominated by starchy staples such as sweet potatoes, yams and taro, rice is an important staple for the approximately 50% of households that consume rice. According to the 2009/10 Household Income Expenditure Survey (HIES), households living in urban areas depend more on rice for overall consumption: urban per capita consumption was nearly 2.5 times that of rural areas (59.2 kg/capita and 24.0 kg/capita, respectively) in 2009/10. Estimated rice consumption for households that do consume rice is relatively high: 67.0 kg/capita/year, equivalent to 685 kcal/capita/day, or 30% of the minimum daily energy requirement of 2250 calories per capita.

Domestic policy changes in response to the spread of COVID-19 have also influenced the supply and demand of marketed food items. Most countries, including PNG, have implemented lockdowns and social distancing policies that require non-essential services such as restaurants, hotels, and offices to temporarily close. In PNG, policies to limit potential risk of contagion include restricted transportation (e.g., roadblocks, permits, restricted flight transportation) and closures of both formal and informal food markets in urban centers and rural areas. These policies have created unemployment among many urban dwellers, as well as restricted rural to urban food supply chains for fresh, domestic agricultural produce.

This article presents a quantitative analysis of the rice economy of PNG utilizing data from the 2018 household survey in several provinces of PNG along with the national 2009/10 HIES data. We present results of simulations of potential impacts of increases in the rice price on the welfare of poor and non-poor households at both the national and regional levels. We focus on two key outcomes of the simulation exercise. First, we evaluate the extent of and variation in the impact of price shocks on rice consumption among urban and rural, poor and non-poor households considering the geographic and related agricultural diversity of PNG. Second, we investigate how domestic policy changes in response to the spread of COVID-19 have impacted the demand for rice in PNG.

We contribute to a sparse literature of food price shock effects on import-dependent, island economies. In addition, given that PNG is characterized by an environment of outdated nationally representative data, this article demonstrates how robust analysis with limited data can inform domestic policy during a significant global shock. Many Pacific countries are implementing policies in reaction to the COVID-19 pandemic with the understanding that potential economic shocks could be devastating for both rural and urban populations; however, these decisions are being made without the tools to evaluate the economic and social tradeoffs of such policies. This article provides an example of how more thorough evaluation of policy measures can aid in difficult decisions, even in a data-scarce environment.

The remainder of this article is organized as follows. Section 2 describes the rice economy of PNG, highlighting household consumption patterns and the evolution of imports over time. Section 3 presents an econometric analysis of rice demand using 2018 household survey data. Section 4 presents model simulations of the effects of world

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1 Analysis by Gibson and Kim (2013) found, however, that because of quality substitution effects, quantity elasticities are overstated.

2 Reliance on rice imports has also shaped trade policy and development initiatives in other Pacific island countries (Foy, 1992). The Pacific region is not alone in this policy choice; countries throughout Africa and Southeast Asia adopted similar strategies at the cost of missed opportunities to diversify into higher value crop production (Dubois et al., 2019; Perez and Pradesha, 2019; van Oort et al., 2015).
rice price shocks and other disruptions. Section 5 summarizes and discusses policy implications.

2 | THE RICE ECONOMY OF PNG

Agriculture remains one of the most important sectors of the PNG economy, with 87% of the population living in rural areas and more than 80% of inhabitants dependent on subsistence agriculture (Bourke & Harwood, 2009; Gibson, 2012). Given PNG’s geographic and climatic diversity, agricultural production varies widely by location. Households living in the highlands depend heavily on sweet potato production to meet consumption demands. In addition, sales of fruits and vegetables from rural highland areas to large cities along the coast provide income to supplement rural consumption. Households in the lowlands of PNG depend on a variety of root crops including sweet potato, taro and yam, with sago contributing an important share to overall calorie intake in the Momase region. Peri-urban gardens outside of major metropolitan areas are also major sources of food supply for urban populations.

Although own production for consumption dominates the food basket in rural PNG, both rural and urban households rely on marketed food items. An important share of protein consumption in rural areas comes from purchased tinned meat and fish. In select locations of the rural Highlands region, PNG’s large mining sector is an important source of employment, and purchased food is even more prevalent. In addition, climatic conditions in the High- lands facilitate production of key agri-food exports including coffee and cocoa, with smallholder farmers reliant on these cash crops. Throughout rural PNG, small and medium-size informal enterprises comprise an estimated 60% of the non-governmental national domestic product (Schmidt, Mueller et al., 2020; Stanley, 2018). With increases in earnings from cash crops, and a growing extractive industry sector, a greater share of households is consuming processed foods like imported rice. Although domestic rice production has increased over the past several decades (primarily in the Markham and Ramu valleys, and Dreikiker area of East Sepik in the lowlands), this expansion was subsidized and supported by the PNG government, as well as foreign direct investment seeking favorable trade terms for imported rice.

2.1 | Rice consumption patterns

Detailed, nationally representative consumption and expenditure data in PNG are sparse and dated. The most recent nationally representative survey is the 2009/10 HIES covering 4191 households, providing detailed information of region-level consumption of rural, urban and metro populations. According to the 2009/10 HIES data, total consumption of rice was 195.5 thousand tons (1.2% higher than average imports in 2009 and 2010), equal to 28.9 kg/capita (Table 1). Almost 30% (28.5) of rice in PNG was consumed in urban areas where per capita consumption was nearly 2.5 times that of rural areas (59.2 kg/capita and 24.0 kg/capita, respectively). In terms of the quantity of rice consumed, overall, non-poor households (the upper 60% in the per capita expenditure distribution) consumed 40.3 kg/capita of rice, 2.7 times more than poor households (14.7 kg/capita).

To supplement the somewhat dated HIES (2009/10), we use the Rural Survey on Food Systems in PNG (PNG-RSFS), implemented by the International Food Policy Research Institute (IFPRI) in 2018, to evaluate more recent trends in household consumption. The PNG-RSFS survey collected rural household survey data from May through July of 2018, in four areas of the country located in: Middle Ramu district of Madang; Maprik and surrounding districts of East Sepik; Nuku district of West Sepik; and South Bougainville of the Autonomous Region of Bougainville (AROB). Three of the survey areas are located in different provinces of the mainland Momase (lowland) region which houses 26% of the country’s total population. The PNG-RSFS data cannot be considered nationally or provincially representative given its limited sampling. However, given the geographic spread of the survey and the variety of lowland agro-ecological zones represented by the four areas, we consider these data to provide the best alternative for rural lowland livelihood classification short of a nationally representative rural household survey. We present modeling results based on the 2009/10 HIES sample cluster, aggregating updated consumption estimates to rural households in the highlands, lowlands (comprises the Southern and Momase regions), and island regions, and aggregating urban and metro areas in all regions, respectively.

According to updated calculations, using the PNG-RSFS 2018 survey and 2020 population estimates5, of the HIES 2009/10, approximately 50% and 35% of rural poor and non-poor calorie consumption, respectively, is derived from roots and tubers (Figure 1). Roots and tubers comprise a smaller share of calories (13% and 11% in poor and non-poor

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3 The HIES 2009/10 used a two-stage stratified cluster sample design with ten strata, including rural and urban areas in four geographic regions (Momase, Highlands, Southern, and Islands). PNG’s two largest cities, Port Moresby and Lae were included in separate metropolitan strata.

4 Schmidt et al. (2019) provides detailed information on the sampling stratification, geographic location, and questionnaire content of the Rural Survey on Food Systems in PNG (PNG-RSFS). Survey data are
### TABLE 1 Estimates of rice consumption in PNG, 2020

| HIES 2009/10④ | 2020 Estimate | 2020 Population |
|---------------|---------------|-----------------|
|               | kg/cap ('000 tons) | Shares b | kg/cap ('000 tons) | (thousands) |
| **Urban**     |                |                |                  |             |
| Poor          | 42.5           | 17.9           | 9.2%             | 49.5        | 26.0 | 525.6 |
| Non-poor      | 72.8           | 37.8           | 19.3%            | 85.5        | 55.0 | 642.9 |
| Total         | 59.2           | 55.7           | 28.5%            | 69.3        | 81.0 | 1168.5 |
| **Rural**     |                |                |                  |             |
| Poor          | 10.2           | 26.6           | 13.6%            | 12.0        | 41.2 | 3447.3 |
| Non-poor      | 35.1           | 113.2          | 57.9%            | 41.0        | 177.8 | 4331.2 |
| Total         | 24.0           | 139.8          | 71.5%            | 28.2        | 219.0 | 7778.6 |
| **All PNG**   |                |                |                  |             |
| Poor          | 14.7           | 44.5           | 22.8%            | 16.9        | 67.3 | 3972.9 |
| Non-poor      | 40.3           | 151.0          | 77.2%            | 46.8        | 232.7 | 4974.1 |
| Total         | 28.9           | 195.5          | 100.0%           | 33.5        | 300.0 | 8947.0 |

Notes: Share of total PNG consumption. Poor is defined as households in the bottom 40% of the per capita expenditure distribution.

**Source:** Authors’ calculations using HIES 2009–10 and IFPRI PNG-RSFS (2018).

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**Figure 1** Estimated total calories per person per day by food category and location in 2020. Source: Authors’ calculation from the PNG Household Income Expenditure Survey (2009/10) and IFPRI (2018) *Note:* “Others” contains the remaining food items including meat, dairy, vegetable and fruit [Color figure can be viewed at wileyonlinelibrary.com]

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households, respectively) per person per day in urban households, whereas rice comprises 30% and 22% of calories per person per day for urban poor and non-poor households, respectively. As expected, non-poor households (both rural and urban) consume a greater share of “other” calories outside of the major staple foods, including meat, vegetables, and fruit.

Table 1 focuses on household rice consumption in 2020. For rural households in the Momase region, estimates are based on data from the PNG-RSFS conducted in 2018 available for download at: https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/ZXRDB6N

④The 2020 population estimates for PNG are sourced from World Bank published estimates.
TABLE 2  Average annual rice consumption (kg/capita) by expenditure quintile

| Survey area    | Household samplea | Expenditure quintile |  |  |  |  |  |  |
|----------------|-------------------|----------------------|---|---|---|---|---|---|
|                |                   | 1 (poorest)         | 2 | 3 | 4 | 5 (wealthiest) | Total |
| AROB           | Consuming         | 44.6                | 51.5 | 73.3 | 79.6 | 124.2 | 71.9 |
|                | All               | 42.2                | 49.5 | 69.0 | 79.6 | 121.0 | 69.3 |
| East Sepik     | Consuming         | 11.3                | 22.3 | 25.4 | 32.0 | 44.8 | 29.4 |
|                | All               | 6.8                 | 17.8 | 21.8 | 27.9 | 43.0 | 24.3 |
| Madang         | Consuming         | 12.5                | 9.3  | 18.8 | 17.3 | 32.4 | 20.6 |
|                | All               | 1.9                 | 3.1  | 4.3  | 8.5  | 14.8 | 6.9  |
| West Sepik     | Consuming         | 10.5                | 13.6 | 42.8 | 26.4 | 64.3 | 34.5 |
|                | All               | 2.5                 | 8.1  | 25.5 | 21.3 | 51.8 | 20.2 |
| Momaseb        | Consuming         | 11.2                | 17.0 | 29.8 | 26.8 | 47.0 | 44.3 |
|                | All               | 3.4                 | 9.8  | 15.3 | 19.5 | 33.0 | 29.4 |
| Total          | Consuming         | 29.1                | 29.6 | 46.5 | 43.5 | 66.4 | 44.3 |
|                | All               | 13.8                | 19.9 | 28.9 | 34.7 | 50.1 | 29.4 |

Notes:

a Consuming sample are households that reported consuming rice, while All refers to the entire survey sample regardless of whether they report eating rice or not.
b Momase includes households from survey sites in East Sepik, Madang and West Sepik.

Source: Authors’ calculations using IFPRI PNG-RSFS (2018).

TABLE 3  Household budget shares by expenditure quintile

| Food type            | Expenditure quintiles | Q1 | Q2 | Q3 | Q4 | Q5 | Poor | Non-poor | All hhds |
|----------------------|-----------------------|----|----|----|----|----|------|---------|---------|
| Wheat/flour products |                       | 1.4| 2.7| 2.3| 3.2| 3.3| 2.1  | 2.9     | 2.6     |
| Rice                 |                       | 6.7| 6.8| 6.9| 6.2| 4.9| 6.8  | 6.0     | 6.3     |
| Starch               |                       | 46.6| 45.2| 45.5| 42.5| 43.5| 45.9 | 43.9     | 44.7     |
| Protein (animal)     |                       | 9.9 | 11.7| 11.2| 14.5| 13.4| 10.8 | 13.0     | 12.1     |
| Fruit                |                       | 2.2 | 2.4 | 2.7 | 2.0 | 1.5 | 2.3  | 2.0      | 2.2      |
| Vegetables           |                       | 4.7 | 3.8 | 4.0 | 3.9 | 3.7 | 4.2  | 3.8      | 4.0      |
| Fats                 |                       | 1.0 | 1.4 | 1.5 | 1.8 | 1.8 | 1.2  | 1.7      | 1.5      |
| Other (including dairy) |                   | 5.0 | 4.8 | 5.2 | 6.0 | 6.2 | 4.9  | 5.8      | 5.4      |
| Food share of total expenditure |   | 77.6 | 78.8 | 79.2 | 80.1 | 78.3 | 78.2 | 79.2     | 78.8     |

Note: Poor is defined as households in the bottom 40% of the per capita expenditure distribution.
Source: Authors’ calculations using IFPRI PNG-RSFS (2018).

(Schmidt Gilbert et al., 2020). Rice consumption in the other regions is estimated using shares of total rice consumption in the non-Momase regions from the 2009/10 HIES. Note that rural per capita consumption in the Momase region in the PNG-RSFS (29 kg/capita/year for all householdsb) is similar to a per capita consumption estimate derived as the share of the region in PNG national consumption in 2009–2010 (.32 times 2020 total consumption of 300 thousand tons (i.e., 96.1 thousand tons, 27.3 kg/capita/year) (Table 2).

Rice consumption in the sampled households of the RSFS (2018) echo consumption patterns reflected in the HIES (2009/10), whereby households with greater expenditures consume greater quantities of rice per capita (Table 2). For example, the poorest rice-consuming households in the East Sepik sample area near Maprik eat, on average, about 11 kg of rice per person per year, whereas the least poor rice-consuming households eat more than four times the amount of the poorest. Including households that do not eat rice, average consumption of poor and non-poor households is 17 and 38 kg per person per year, respectively. In addition, Table 2 demonstrates the variation in rice consumption by region, whereby households in AROB consume substantially more rice per capita in all expenditure quintiles compared to households in other survey areas.

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Food accounts for more than three-quarters of overall household expenditures in poor and non-poor households (Table 3). The PNG-RSFS (2018) underlines the
FIGURE 2 Rice consumption by kilometer distance to nearest major market town. Note: Major market towns for each area include: Wewak (East Sepik), Maprik (East Sepik), Nuku (West Sepik), Madang (Madang), Keta (Bougainville), Arawa (Bougainville), Buka (Bougainville); Households with implausible rice consumption per capita have been excluded. Source: Authors’ calculations using IFPRI–RSFS (2018) [Color figure can be viewed at wileyonlinelibrary.com]

it is important to note, however, that estimating household expenditure values from reported food consumption data can introduce measurement error given the significant challenges to valuing the true cost of consumed items in subsistence and low-income households. Previous work has shown that consumption recall of subsistence households, as well as lack of data on direct purchases of staple crops within subsistence agriculture households may lead to measurement error resulting in an underestimate of household consumption values (Zezza et al., 2017).

Using the PNG-RSFS sample, we evaluate rice consumption differences by proximity to a major market town. Similar to the HIES, the PNG-RSFS data suggest that households that are further away from a market consume less rice (Figure 2). The household sample in Madang district is located in the remote, Middle Ramu sub-district, and illustrates how rural consumption baskets differ based on access to a market. Recognizing the dependence on locally produced food items in rural areas of PNG, an (imported) food price shock will have, on average, larger effects on urban and peri-urban households.

2.2 PNG Rice imports

Estimates of PNG rice imports are available from 2001 to 2016 via BACI, a database that attempts to reconcile export and import data from national data sources (Gaulier & Zignago, 2010). BACI data for quantity and value of PNG rice imports show a long-term upward trend, interrupted by 4 years of low volumes and value of imports from 2011 through 2014 (Figure 3). Informal data from the PNG rice trade suggests that current (early 2020) rice imports are about 25,000 tons per month, equivalent to approximately 300,000 tons/year, consistent with the overall trend in Figure 3. Vietnam, Thailand, and the United States were the major exporters of rice to PNG between 2009 and 2016, accounting for 37%, 28%, and 21% of the quantity of PNG rice imports in this period.

International rice prices have increased in world markets in 2020. Between December 2019 and May 2020, the export price (fob) of Bangkok A1 Super (a commonly traded medium quality rice) rose by 26% and the export price of Vietnam 5% broken rose by 30%. These price increases in early 2020 reflected Vietnam’s announcement of rice export restrictions and Cambodia’s ban on white rice exports in response to the COVID-19 outbreak. Likewise, despite India’s large rice stocks and no formal export ban, logistics challenges due to shelter-in-place policies to curb COVID-19 contagion substantially delayed rice shipments and supply chain logistics. The increases in rice price in both Vietnam and Thailand persisted in subsequent months as well: the average price of rice from these two sources from March through September 2020 was 25% higher than the price in December 2019. In the next section, we evaluate household demand for rice to estimate own-price elasticity of rice demand which is incorporated in the simulation model presented in Section 4.
one of the Heckman two-stage estimator employs a probit model that determines the probability that a given household consumes rice. Predicted values from the first-stage probit equation are retained as to allow an estimation of the inverse Mills ratio for each observation which is used as an instrument in the second stage.

The desired consumption (share of expenditure on rice) equation which causes sample selection, is specified as

$$C^*_j = \gamma' z_j + u_j$$  \hspace{1cm} (1)

where $C^*_j$ is household consumption on rice, $z_j$ is a vector of variables associated with rice consumption, which is only observed if the household reported eating rice, and $u_j$ is the error term with a bivariate normal distribution with zero mean. The variable $C^*_j$ is not observed, but households report whether they consumed rice or not, so that

$$C^*_j = 1 \text{ if } C^*_j > 0$$

and

$$C^*_j = 0 \text{ if } C^*_j \leq 0$$

Let $w_j$ represent the share of total expenditure dedicated to rice by each household:

$$w_j = \beta' x_j + \varepsilon_j,$$  \hspace{1cm} (2)

whereby, $x_j$ is the vector of variables affecting household rice consumption and $\varepsilon_j$ is the error term with a bivariate normal distribution with zero mean. Under the assumption that the error terms are jointly normal, the
second-stage linear regression is defined as

$$E(W_j|C_j = 1) = E(W_j|C_j > 0) = E(W_j|u_j) - \gamma'z_j$$

$$= \beta'x_j + E(\varepsilon_j|u_j) - \gamma'z_j$$

$$= \beta'x_j + \rho \sigma \lambda_j(\alpha_u)$$

(3)

To correct for potential sample bias, the ordinary least squares (OLS) regression represented in Equation (3) includes a vector of independent variables $X$ and the inverse Mills ratio $\lambda_j(\alpha_u)$ as regressors in order to estimate $\beta, \rho$. $\rho$ is the correlation between the error terms (i.e., between unobserved determinants of the probability of eating rice, $u$, and the unobserved determinants of the share of rice expenditure in household total expenditure, $\varepsilon$), and $\sigma$ is the standard deviation of the error term $\varepsilon$.

### 3.2 Results

In total, the PNG-RSFS sample comprises 1026 households, of which 1012 had sufficient data for analysis of rice consumption. The household survey collected detailed consumption and expenditure information on weekly consumption of a detailed list of food items, as well as monthly and yearly non-food expenditures. Households were asked whether they consumed rice, and if so, how much rice was consumed during the last 7 days and where they sourced their rice (harvested, purchased, or gifted). Data collection spanned 3 months (May–July 2018) and was located in areas of the country that have non-seasonal agricultural production practices.\(^{10}\)

Table 4 summarizes values of the relevant variables used for this analysis. The selection of variables used in the Heckman two-stage procedure is suggested by other studies and adapted to the unique characteristics of PNG (Alderman, 1987; Burton et al., 1994; Hoffmann & Kassouf, 2005; Kojima et al., 2011; Madden, 2008). In the first (probit) equation of the Heckman two-stage model, participation (whether a household consumed rice in the past 7 days) largely depends on household characteristics. We hypothesize that access to markets and ability to travel to a market are important indicators of participation. Poor security within PNG (particularly for women), lengthy travel times, and inadequate transportation infrastructure suggests that the sex and age of the household head, and distance to the nearest major market town would affect the decision of whether a household travels to purchase rice and other foodstuffs.\(^{11}\) Recognizing time-use tradeoffs of traveling to a market, we include household size and number of household dependents in the first-stage regression as well. We also assume that total household expenditure, educational attainment of the household head, and the price of rice is associated with household participation via household income and opportunity costs. We include the unit price of sweet potato in both the first and second stage of the regression to consider substitution effects among staple crops. Finally, we include a set of province dummies to control for geographic variations and consumption preferences.

In the second-stage (quantity of rice consumption) equation, total household expenditure and unit prices of rice and sweet potatoes are the principal covariates we evaluate for this analysis. Total household expenditure and unit rice price coefficients derived in the second-stage regression are used to calculate the expenditure and own-price elasticities, respectively, employed in the partial equilibrium model discussed below.

Total household expenditure includes the value of both non-food and food (purchased and non-purchased) consumption and expenditure, and is used as the proxy for household income for several reasons. First the IFPRI survey comprises predominantly rural households whereby over half of the surveyed households reported that their sole source of income was from subsistence farming (barter and trade remain common practice in rural communities in PNG). Second, other forms of income earned via wage work (reported by less than 5% of households) and non-farm enterprises (approximately one-third of households) fluctuate based on the opportunity costs of working off-farm versus planting and harvesting food for the household.\(^{12}\) Finally, given the rural nature of the household survey data, most households reported that they had no access to credit or savings options via lenders or banks.

The unit price of rice is constructed from data collected in the household survey on purchased food items. For households that consumed and purchased rice, the reported unit cost (PGK/kg after conversion to kilogram units) is used. For households that did not purchase rice, we use the median of all (consistent unit) price data by food item within a community and assign each household

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\(^{10}\) Bourke and Harwood (2009) provide a detailed description of geography and associated crop production differences, considering rainfall and elevation across the landscape of PNG. Most lowland areas in PNG, and all of the survey areas included in the PNG-RSFS are considered non-seasonal, whereby sweet potato, yam, sago, and other staple crops are produced and harvested year around. This was also reflected during survey scoping visits and focus-group data collection activities.

\(^{11}\) The inclusion of these variables may be justified on several grounds. For example, age may be associated with consumer preference, whereby older households prefer less labor-intensive crops (i.e., purchase rice compared to harvesting customary staple crops).

\(^{12}\) Previous studies have shown, particularly in contexts such as PNG, that total expenditure is a more reliable measurement of household income (Browning et al., 2014; Schmidt, Gilbert et al., 2020; Zezza et al., 2017).
within the respective community the same community rice price.  

In addition to total household expenditure and unit price, we also include household size and number of dependents assuming that household composition and size may affect purchase volume. Finally, we maintain the set of province-level dummies in the second-stage regression to control for area-specific factors that may drive the quantity of rice consumption.

To correct for selection bias using the Heckman two-stage model, an exclusion restriction is required whereby at least one variable which appears in the first-stage participation equation is absent in the second-stage levels equation. Throughout all specifications we assume that

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**Table 4** Descriptive statistics of covariates included in Heckman model by rice and non-rice consuming households, Mean (SD)

|                           | All households | Rice consuming households | Non-rice consuming households | T-test |
|---------------------------|----------------|----------------------------|--------------------------------|--------|
| Household budget share of total expenditure for rice | 6.30 (8.24) | 9.50 (8.49) | .00 (.00) | .000 |
| Log of total household expenditure (PGK/capita/year) | 7.35 (.68) | 7.44 (.64) | 7.18 (.71) | .000 |
| Log of household-level unit rice cost (PGK/g) | 8.51 (.46) | 8.40 (.50) | 8.74 (.24) | .000 |
| Log of household-level unit sweet potato cost (PGK/g) | 7.04 (1.25) | 7.30 (.97) | 6.52 (1.54) | .000 |
| Household size | 5.91 (2.22) | 5.75 (2.17) | 6.22 (2.29) | .001 |
| Sex of household head is female | .10 (.30) | .09 (.28) | .13 (.34) | .024 |
| Age of household head | 42.23 (11.77) | 42.86 (11.95) | 40.98 (11.32) | .016 |
| Years completed education of household head (0-16) | 6.61 (3.63) | 7.12 (3.60) | 5.60 (3.46) | .000 |
| Number of household dependents (15 > age > 65) | 2.83 (1.70) | 2.67 (1.61) | 3.15 (1.83) | .000 |
| Euclidean distance to major market town (km) | 55.10 (49.01) | 42.95 (39.62) | 79.02 (56.41) | .000 |
| Bougainville (0/1) | .25 (.43) | .36 (.48) | .03 (16) | .000 |
| East Sepik (0/1) | .24 (.43) | .30 (.46) | .12 (.33) | .000 |
| Madang (0/1) | .29 (.45) | .14 (.35) | .57 (.50) | .000 |
| West Sepik (0/1) | .23 (.42) | .20 (.40) | .28 (.45) | .003 |
| **Number of Households** | 1012 | 671 | 341 |

*Note: PGK = Papua New Guinea Kina; T-test p-value is derived from a t test of equal variances, standard deviations are presented below in brackets.

*Major market towns for each area include: Wewak (East Sepik), Maprik (East Sepik), Nuku (West Sepik), Vanimo (West Sepik), Madang (Madang), Kieta (Bougainville), Arawa (Bougainville), Buka (Bougainville); USD 1.00 = PGK 3.28 in June 2018.

*Source: Authors’ calculation using IFPRI PNG-RSFS (2018).
distance to a market is associated with a household’s decision to consume rice, but once that decision is made, distance does not directly influence the amount purchased or consumed. Additional exclusions include the characteristics of the household head (sex and age). In addition, we assume that years of education of household head may be associated with whether to purchase rice (related to the opportunity cost of labor for own production of staple crops), but not on the amount purchased or consumed. We test these exclusion assumptions and results show that adding these covariates iteratively to the second-stage regression has little effect on overall results (sensitivity results to the exclusion restriction are provided in Appendix Table 1).

Table 5 presents the coefficients for the first-stage probit equation and the second-stage levels equation. We compare the coefficients for the levels equation estimated without correcting for selection bias (column B), and estimated by Heckman’s procedure (column C). The coefficients for the uncorrected consumption equation (column B) consider only those households that consumed rice, not correcting for sample selection bias—hence the total observations are equal to the censored sample of 671 households. Correcting for selection bias via the Heckman procedure (column C) suggests that the factors influencing households’ decision to consume rice may differ from the factors influencing how much rice households consume (measured as the share of total expenditure spent on rice). Conditional and unconditional marginal effects calculated at the mean are presented in columns D and E, respectively. The conditional marginal effect estimates the effect of a covariate among consumers (those that reported a positive value of rice expenditure) during the survey period. The unconditional marginal effect reflects the sum of the effect of a covariate, accounting for the increased probability of consumption and correcting for sample selection bias using the Heckman two-stage estimator.

Results from the probit equation show a positive and significant coefficient for total household expenditure and household head education (Table 5). Higher total expenditures are associated with a greater probability of consuming rice. This is expected given that almost all consumed rice in PNG is purchased. As expected, the probit equation demonstrates that the probability of consuming rice decreases as the unit rice price increases. A higher level of education attained by the household head is associated with a higher probability of consuming rice, which suggests that households with higher levels of education face greater opportunity costs of dedicating labor to own-harvest agricultural or food preparation activities.

The distance to the nearest major market town is negatively correlated with the probability of consuming rice; however, quantitatively this association is small and it loses significance when we test for joint significance with the quadratic term. This is most probably due to the collinearity of the region-level dummy given the clustered survey sampling approach used to randomly select survey communities for data collection. Given limited information on market towns with reliable rice supply, we use a distance measure to larger market towns; however, it is possible that more detailed information about market accessibility, including smaller markets, could improve this estimate. Further evaluation of rice consumption by survey area and distance to a market suggests that the Bougainville sample may be driving this result. Almost all households in Bougainville (96% of households in Bougainville, comprising 24% of rice-consuming households in the total sample) depend on rice to satisfy calorie needs regardless of distance to a market.

We include the unit price of sweet potato (an important staple crop in much of rural PNG) as a covariate in the first and second-stage regression to test for potential substitution effects that may be present in the decision to consume rice. While sweet potato prices do not have a significant effect in the selection (probit) equation of whether to consume rice, an increase in sweet potato prices does have a positive and significant relationship on rice share of total expenditure in the second-stage levels regression suggesting that households would face trade-offs in what staple to buy depending on price (controlling for other factors).

The region-level dummy coefficients in the probit regression are also telling in terms of controlling for variation in household consumption baskets. Two factors may be at play here. First, compared to the most remote survey area in Madang (for which the dummy variable was omitted), South Bougainville is the most connected survey site to major markets. Second, agricultural production in South Bougainville is more export oriented. South Bougainville is heavily focused on cocoa and copra production, necessitating substitution of otherwise harvested staple foods. Similar to Madang survey sites, West Sepik households are remote and rely predominantly on subsistence agriculture.

Results suggest that an increase in unit rice price has a statistically significant inverse relationship (-1.438) with the rice share of total household expenditure when evaluating the unconditional marginal effects. Similarly, as total household expenditure increases, the share of total household expenditure dedicated to rice decreases. This is consistent with Bennett’s law whereby increases in household income lead to a shift away from starchy staples in lieu

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14 Eliminating the quadratic term from the second stage regression results in the linear distance measure becoming insignificant.
15 Gibson and Rozelle (2003) used a detailed rural road dataset and travel time analysis to show that improved rural road access has a significant and positive impact on household income, particularly in poor households, in Papua New Guinea.
Table 5  Heckman sample selection model for rice expenditure share of total household budget

| Variables                                                                 | Participation equation (Probit) | Consumption equation Without correction | Consumption equation Heckman procedure | Marginal effects Conditional marginal effects | Marginal effects Unconditional marginal effects |
|--------------------------------------------------------------------------|----------------------------------|----------------------------------------|--------------------------------------|---------------------------------------------|-----------------------------------------------|
|                                                                          | A                                | B                                      | C                                    | D                                           | E                                             |
| Log of total household expenditure (PGK/capita/year)                     | .583***                          | −3.981***                              | −4.749***                            | −3.840***                                   | −1.122***                                     |
|                                                                          | (.081)                           | (.484)                                 | (.742)                               | (.753)                                      | (.531)                                        |
| Log of household-level unit rice price (PGK/g)                          | −.638***                         | 1.115*                                 | 1.641**                              | .645                                       | −1.438                                        |
|                                                                          | (.185)                           | (.616)                                 | (.737)                               | (.789)                                      | (.895)                                        |
| Log of household-level unit sweet potato price (PGK/g)                   | −.088                            | .627                                   | .790*                                | .652                                        | .222                                          |
|                                                                          | (.056)                           | (.428)                                 | (.443)                               | (.452)                                      | (.401)                                        |
| Household size                                                          | .052                             | −.226                                  | −.297                                | −.216                                      | −.004                                         |
|                                                                          | (.036)                           | (.195)                                 | (.203)                               | (.211)                                      | (.210)                                        |
| Sex of household head is female                                         | −.233                            |                                       |                                      | −.364                                      | −.974                                         |
|                                                                          | (.170)                           |                                        |                                      | (.265)                                     | (.717)                                        |
| Age of household head (years)                                           | −.002                            |                                       |                                      | −.004                                      | −.010                                         |
|                                                                          | (.005)                           |                                        |                                      | (.008)                                     | (.020)                                        |
| Years completed education of household head (0–16)                       | .036**                           |                                       |                                      | .057**                                     | .152**                                        |
|                                                                          | (.014)                           |                                        |                                      | (.022)                                     | (.062)                                        |
| Number of household dependents (15 > age > 65)                          | .026                             | −.103                                  | −.130                                | −.090                                      | .009                                          |
|                                                                          | (.044)                           | (.258)                                 | (.261)                               | (.270)                                      | (.269)                                        |
| Euclidean distance to major market town (km)a                           | −.013*                           |                                       |                                      | −.021*                                     | −.056*                                        |
|                                                                          | (.008)                           |                                        |                                      | (.012)                                     | (.033)                                        |
| Euclidean distance to major market town (km)a squared                    | .000                             |                                       |                                      | .000                                       | .000                                          |
|                                                                          | (.000)                           |                                        |                                      | (.000)                                     | (.000)                                        |
| Region dummy (Madang omitted)                                            |                                  |                                       |                                      |                                            |                                               |
| Bougainville (0/1)                                                      | 2.114***                         | 6.562***                               | 3.099                                | 6.396**                                    | 11.157***                                     |
|                                                                          | (.356)                           | (1.285)                                | (2.809)                              | (2.861)                                     | (2.003)                                        |
| East Sepik (0/1)                                                        | .940**                           | −.356                                  | −3.143                               | −1.678                                      | 1.571                                         |
|                                                                          | (.420)                           | (1.299)                                | (2.390)                              | (2.479)                                     | (2.296)                                        |
| West Sepik (0/1)                                                        | .201                             | .928                                   | −.843                                | −.530                                      | .208                                          |
|                                                                          | (.442)                           | (1.328)                                | (1.838)                              | (1.963)                                     | (2.271)                                        |
| Inverse Mills (Lambda)                                                  | −3.349                           |                                       |                                      |                                            |                                               |
|                                                                          | (2.401)                           |                                        |                                      |                                            |                                               |
| Constant                                                                | 1.589                            | 24.337***                              | 28.583***                            |                                            |                                               |
|                                                                          | (1.839)                           | (7.272)                                | (8.003)                              |                                            |                                               |
| N Observations                                                          | 1012                             | 671                                    | 1012                                 | 1012                                       | 1012                                          |

Note: Standard errors in parentheses.

* Major market towns for each area include: Wewak (East Sepik), Maprik (East Sepik), Nuku (West Sepik), Vanimo (West Sepik), Madang (Madang), Kieta (Bougainville), Arawa (Bougainville), Buka (Bougainville).

** Not corrected using Heckman procedure using censored sample of non-zero observations of rice expenditure.

*** p < .01.

** p < .05.

* p < .1.

Source: Authors’ calculation using IFPRI PNG-RSFS (2018).
of more protein and vitamin-rich (and more expensive) foods. The coefficient on household head education is positively associated with the share of rice expenditure, suggesting that its inclusion in the second-stage regression may be necessary. We test this specification (see results in Appendix Table 1) and find that the education of the household head is not significant with regard to the rice budget share when controlling for other factors.

The coefficient $\beta$ of 1.641 on the logarithm of household-level unit rice price in the Heckman second-stage regression (Table 5) implies an own-price elasticity of -.740 (equal to $\beta$ divided by the average rice budget share ($w$) of consumers of 6.3% minus one). In the simulations that follow, we use the $\beta$ coefficient and the mean budget shares ($w$) of poor and non-poor households to calculate own-price elasticities ($= \beta/w - 1$) of -.758 and -.726 for the poor and non-poor, respectively. We use the coefficient on the logarithm of total expenditures $\beta_\gamma$ (-4.749) to calculate expenditure elasticities ($= 1 + \beta_\gamma/w$) of .298 and .207, for the poor and non-poor, respectively.\(^{16}\)

4 | IMPACTS OF WORLD PRICE SHOCKS AND INCOME SHOCKS ON HOUSEHOLD CONSUMPTION

4.1 | Model structure

We use a simple partial equilibrium model of PNG’s rice economy adapted from Dorosh (2001) and Coady et al. (2009) to estimate the effects of world price changes and other shocks on rice consumption and household welfare. The model simulations presented here assume an integrated rice market for PNG in which percentage changes in domestic rice prices are the same for all households across the country.

In the model, the domestic price of rice is set equal to the exogenous import price of rice plus fixed domestic marketing costs. In each simulation, the percentage changes in rice consumption for each household are calculated as the household’s own-price elasticity of demand for rice times the percentage change in the rice price. Total demand for rice, equal to the sum of demand by all households, determines the volume of imports. Given that domestic production of rice accounts for only about six thousand tons, or approximately .2% of total supply, changes in domestic production have little effect on the results in the simulations presented below, reducing imports by less than .1%. Household incomes are set exogenously given that incomes from rice production account for a negligible share of income of any of the household groups specified in the model. (Appendix Table 2 lists the equations and variables in the model.)

We estimate COVID-19 shocks to household incomes using mobility data from Google (2020) that provide an indication of activity in various sectors.\(^{17}\) Using the percentage change in mobility in various categories relative to January 3 to February 6, 2020, we construct low and high estimates of income shocks for broad household groups (Appendix Figure 1 and Appendix Table 3). Thus, for the urban poor, we use the average reduction in activity observed between January and the average of March through August in retail and recreation, parks and transit stations (9.8%) as the low estimate of their income loss. We use the reduction in activity in transit stations (20.0%) as the high estimate of their income loss. For the urban non-poor, we use the average reduction in transit stations and workplaces (-4.1%) as the low estimate for income losses; for rural households, our low estimate is zero. For both the urban non-poor and rural households, the high estimate is 9.8% (the same as the low estimate for the urban poor).

4.2 | Simulation results

Table 6 presents the simulation results of a 25% increase in the world price of rice, equal to the increase in world prices from December 2019 to the average March-September 2020 price. Simulation 1 models the effects of the price hike with no income shock and Simulations 2 and 3 model the effects of low and high estimates of household income shocks discussed above. Simulation 4 shows the effects of the shocks modeled in Simulation 3, but uses more inelastic demand parameters (equal to .7 times those in Simulation 3), since the econometric estimates using cross-section data may overstate responsiveness of demand in the short run.

The 25% increase in the world price of rice with no household income shock results in a 14.3% decline in demand for rice and an increase in the rice import bill from US$ 254.9 million to US$ 269.5 million (Simulation 1). Poor consumers (those in the bottom 40% of the income distribution) suffer a net welfare loss of US$ 19.5 million (US$ 4.90 per capita, equivalent to 1.3% decrease of a 1 US dollar per day income).\(^{18}\) The household groups with the largest rice consumption, Rural Lowlands (Southern and Momase rural areas) and Other Urban (comprise urban areas of all

\(^{16}\) Thus, although the estimated values of the coefficient $\beta_\gamma$ are negative, the expenditure elasticities are positive.

\(^{17}\) See Sampi and Jooste (2020) for another example of the use of Google mobility data to estimate economic losses.

\(^{18}\) At the prevailing exchange rates of 2018 (USD 1.00 = PGK 3.28), the average income of households below the poverty line in the 2018 IFPRI survey was 4.14 Kina (1.23 US$/day). Approximately 50% of the population (from the PNG-RSFS) and 40% of the population (from the HIES 2009/10) live at or below the poverty line.
TABLE 6  Effects of increases in world rice prices: PNG modelsimulation results

|                        | Base  | Sim 1 | Sim 2  | Sim 3  | Sim 4  |
|------------------------|-------|-------|--------|--------|--------|
| Household Income Shock (%) | .0%   | −2.8% | −11.9% | −11.9% |
| Production Rice ('000 tons) | .6    | .6    | .6     | .6     |
| Imports ('000 tons)     | 300.0 | 256.8 | 255.8  | 250.1  | 264.1  |
| Total Supply (Demand) ('000 tons) | 300.6 | 257.4 | 256.4  | 250.7  | 264.7  |
| Rice Consumption (% change) | — | −14.3% | −14.7% | −16.6% | −11.9% |
| Urban Poor             | 26.1  | −14.8% | −17.4% | −20.4% | −14.7% |
| Urban non-poor         | 55.1  | −14.2% | −15.0% | −16.0% | −11.5% |
| Rural Poor             | 41.3  | −14.8% | −17.4% | −17.4% | −12.7% |
| Rural non-poor         | 178.1 | −14.2% | −14.2% | −16.0% | −11.5% |
| Value of imports (mn$) | 254.9 | 269.5 | 268.4  | 262.5  | 277.2  |

Net Benefits (Poor HHs) (mn$)

|                        | — | — | — | — | — |
| Metro                  | — | −3.13 | −3.09 | −3.04 | −3.13 |
| Other Urban            | — | −4.40 | −4.34 | −4.27 | −4.40 |
| Rural Lowlands - Main  | — | −4.88 | −4.81 | −4.81 | −4.94 |
| Rural Highlands - Main | — | −3.66 | −3.61 | −3.61 | −3.70 |
| Rural Islands          | — | −3.39 | −3.34 | −3.34 | −3.41 |
| Total Poor             | — | −19.46 | −19.39 | −19.06 | −19.59 |
| US$/capita (poor households) | — | −4.90 | −4.83 | −4.80 | −4.93 |
| As share of $1/day income | — | −1.3% | −1.3% | −1.3% | −1.4% |

Notes: Own-price elasticities of demand: (poor: -0.758, non-poor: -0.726); Income elasticities of demand: (poor: 0.298, non-poor: 0.207).

Source: Model simulations.

regions except Port Moresby and Lae metro centers) suffer losses of US$ 4.9 million and US$ 4.4 million, respectively.

Including the effects of low (-2.8%) and high (-11.9%) estimates of income shocks due to the slowdown in the PNG economy linked to COVID-19 restrictions on movement of people and goods, rice consumption falls by 14.7% and 16.6%, respectively. Rice consumption of the urban poor drops more steeply than for other household groups (-20.4% in Simulation 3) because of the larger income shock for these households. The welfare losses due to the shocks for all poor households together are slightly smaller than in Simulation 1 (e.g., US$ 19.1 million in Simulation 3 as compared with US$ 19.6 million in Simulation 1) because of the downward shift in demand (i.e., lower rice consumption) caused by the income shock.19

With a more inelastic price elasticity of demand, rice consumption of poor consumers falls less, by only 11.9% in Simulation 4, in comparison with a decline of 16.6% in Simulation 3. Welfare losses for the poor, equal to US$ 19.6 in Simulation 4, are only slightly larger (2.8%) than in Simulation 3, however.

5  | POLICY IMPLICATIONS AND CONCLUSIONS

Since December 2019, just before the onset of the COVID-19 pandemic, international rice prices rose steeply—by 26% for Bangkok A1 Super rice and 30% for Vietnam 5% broken rice. Given that essentially all of PNG’s rice supply comes from rice imports (estimated to be about 300 thousand tons/year), the domestic price of rice in PNG has increased in local urban markets.

Although rice is not the major staple in PNG, on average, it still accounts for 14% of total calories and about 6% of total household expenditures (including the value of own consumption of other foods) in the 2018 IFPRI rural household survey. Furthermore, the 2009–2010 HIES indicates that despite the considerable marketing costs for delivering imported rice from seaports to local markets, 52.4% of the population in that year lived in households that held rice stocks.

In this article, we use data on the shares of regional household rice consumption from the 2009–10 HIES, household rice consumption in lowland rural areas from the 2018 IFPRI Rural Survey on Food Systems (PNG-RSFS) and international trade data on imports to estimate household rice consumption for various regions...
of PNG. The 2018 PNG-RSFS data are also used to econometrically estimate the responsiveness of household rice demand to changes in incomes and rice prices.

Model simulations indicate that a 25% rise in the world price of rice (approximately equal to the actual increase in world rice prices through September 2020) is expected to decrease overall rice consumption in PNG by 14%, and reduce rice consumption of both poor and non-poor households by a similar percentage. Including the effects of estimated 3% to 12% declines in household incomes because of the COVID-19 related economic slowdown, total rice consumption falls by as much as 17%. For the urban poor whom incomes likely are most affected, the drop is steeper: 20%. Because domestic rice production in PNG is only .6 million tons (.2% of supply), however, changes in production have little effect on imports or incomes. Overall, the welfare loss to poor households is about US$ 20 million. Note that this estimate focuses on the welfare effect associated with a rice price increase; however, the overall welfare effect due to a contraction in the economy (considering all sectors) would be much larger.

While PNG produces a very small share of rice for domestic consumption (PNG does not export rice), a variety of research on rice production potential in PNG suggests that significant rice production expansion is unlikely to be profitable or sustainable. It is unclear whether it is economically or politically feasible to expand rice production due to: difficulties in accessing land that is not under customary tenure, opportunity costs of developing rice production in lieu of higher value tree-crop exports (Gibson, 1993), and tradeoffs of lost employment in less labor-intensive rice production compared to other export crop activities (Gibson, 1994).

Investment in improved data systems are also needed to provide real-time analysis on market supply and demand. Currently, although a variety of institutions are collecting food price data, there is no central repository or database that can be easily drawn upon to monitor food price changes in the market over time. Small surveys of wholesale traders and regular monitoring of prices of rice and other food commodities would also enhance the ability of all actors in rice and other key food value chains to respond to shocks quickly and efficiently. Finally, there is a need for an updated national household survey to provide up-to-date information on household incomes and expenditures across all geographies of PNG to better inform policy and development assistance. Given that per capita rice consumption has risen by over 20% since the 2009/10 national household survey, updated data on regions outside the areas covered in the 2018 IFPRI survey are needed for further analysis of rice markets, as well as broader national food policy.

A targeted food or cash transfer could also be considered, not only to offset negative impacts of a rice price shock, but other potential shocks, as well. Currently, PNG does not have a social safety net program for vulnerable households. Instead, almost 60% of the rural households in the 2018 IFPRI survey reported that they rely on assistance from their wantok (kinship group) as their main coping strategy. Some form of targeted safety net, perhaps with a work requirement for households with members able to work (such as in Ethiopia’s Productive Safety Net Program) may be a workable model that could be tested, initially through small projects that include rigorous impact evaluations.

Finally, lack of information dissemination to rural farmers regarding travel restrictions has disrupted agricultural trade as goods transported on major corridors are confiscated and farmers and traders are prevented from reaching their destination. Disruptions of supply chains of locally produced foods threaten to magnify the negative impacts of world rice price increases on household access to food. Appropriate mechanisms to implement public health measures restricting mobility may be needed; however, these policies should try to minimize domestic market disruptions where possible.

The worldwide COVID-19 crisis has affected food security for households in PNG both through disruptions in trade in international markets, as well as reduced economic activity and resulting income losses domestically. Although, PNG’s food economy is heavily dependent on non-traded starchy staples, significant consumption of imported goods, particularly rice, make it vulnerable to international price shocks. A return to lower international rice prices will benefit poor households, particularly those in urban areas, but longer-term investments in production, information systems, markets and broader safety nets are needed to achieve sustained improvements in food security.

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20 However, PNG’s largest supplier of rice, Trukai Industries Ltd., has partnered with PNG to provide technical expertise and support to expand domestic rice production (particularly in the East Sepik and Markham valley). Similarly, PNG has explored opportunities to link with Indonesia’s Naima Agro Industries to develop large-scale mechanized rice farms in return for favorable trade terms for rice imports (with promises of reserving up to 80% of rice imports for the Indonesian company).
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**SUPPORTING INFORMATION**
Additional supporting information may be found online in the Supporting Information section at the end of the article.

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