Analyzing the effect of rice price on rice farming household's income through a mixed-frequency data approach

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Synopsis

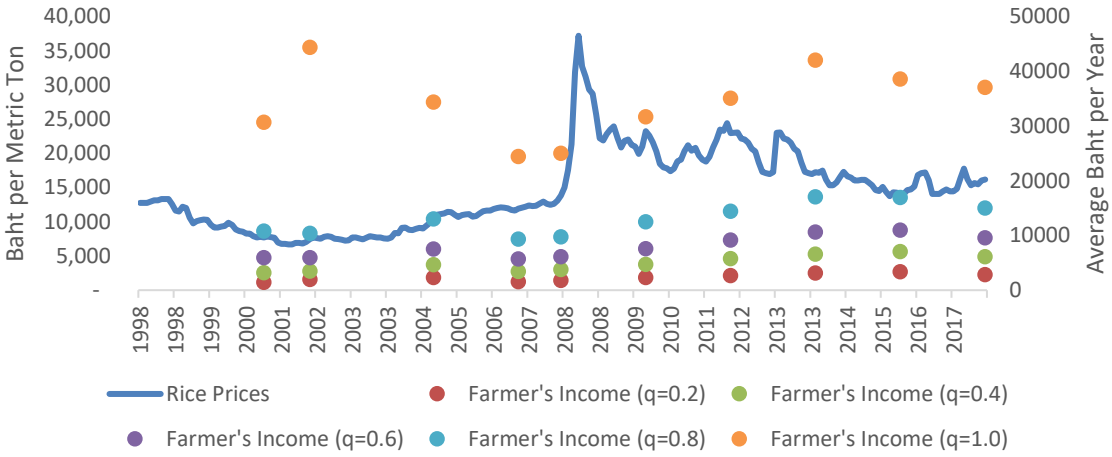
- Many developing economies use rice prices as a political tool because they believe that higher prices lead to higher income.
- This common perception may not always hold true in Thailand as higher prices do not always lead to better income for all rice farmers.
- Hence, using rice prices as a political tool can be ineffective and useless, especially when low-income households are targeted.

Introduction

The perception that higher rice prices lead to higher rice farmer income appears to be common. Hence, rice price has become a political tool in many developing economies. For instance, in 2022, Thailand's agricultural sector accommodated approximately 8.038 million households, including small-scale farming, commercial farming, and high-value agriculture, with rice accounting for 55 percent of household farming activity (Ministry of Agriculture and Cooperatives, 2022). Because of this high reliance, the majority of rice farmers' income may be determined by the rice price. Figure 1 supports this argument at first glance because farmers' income in most quantiles tends to move in the same direction as rice price. However, the movement depicted does not reflect the causal relationship between these two variables. Furthermore, whether this relationship exists across all income quantiles remains questionable. This kind of effect has rarely been discovered quantitatively and is usually presumed to be common knowledge and left untouched.

Discussion of this argument can start with the study of the food price effect on farmer's welfare. Deaton (1989), Budd (1993), and Barrett (1997) found that higher rice prices are likely to bring benefits to rural households, which is consistent with the common belief in economics. Accordingly, some other studies have attempted to measure the welfare gain or loss from the changing prices (Ackah and Appleton, 2007; Wood et al., 2009; Attanasio et al., 2013; Kane et al., 2015; Ojogho and Ojo, 2017). Surprisingly, primary data and scenario-based analyses are the main methods used in these studies. This raises the question of why secondary-data were not used.

Figure 1: Rice Prices and Rice Farmers' Income by Quintile



Sources: (1) Thai Rice Exporters Association for monthly rice prices and (2) Socio-Economic Survey, National Statistical Office for biennially rice farmer' income

The possible cause is estimation difficulties due to the different frequencies of price and income data. In our case, rice prices are available monthly from the Thai Rice Exporters Association, whereas income data are available biennially (or every other year) from the Socio-Economic Survey by the National Statistical Office.[1] Obviously, the frequency mismatch between the higher-frequency rice prices and the lower-frequency farmers' income is the real challenge of the secondary-data analysis of this issue. However, note that regardless of the data frequency, all rice farming households face the same world-market price in practice.

To overcome this issue, we used a mixed-frequency data technique (MIDAS) to analyze the relationship between rice prices and farmers' income. This technique was first developed by Ghysels et al. (2004), who extended a traditional time-series model with input variables that need not be standardized at the same frequency. The MIDAS is useful for dealing with different-frequency data and preventing high-frequency information from being lost. However, to aggregate the high-frequency data, MIDAS requires a weighting scheme. Some weighting schemes can be complicated and cause estimation problems. Therefore, Foroni et al. (2015) developed an unrestricted MIDAS model (U-MIDAS) for estimation with no weighting schemes. In other words, the U-MIDAS is a traditional time-series model with different-frequency data. Experiences from other applications show that MIDAS, either restricted or unrestricted, outperforms the standard time-series model in both in-sample fits and out-of-sample forecasting (Wichitaksorn, 2022).

Using mixed-frequency data techniques, we attempt to estimate the rice price effect on farmers' household income in this study. We examine how households with varying (quantile) income levels respond to the price. The analysis's quantitative effect and insights will help us better understand the matter and design more effective, relevant policies. This study also has a research implication: the analysis of welfare gain and loss from changing rice prices.

Data and Methodology

[1] Although the Labor Force Survey (LFS) is available quarterly, the data do not cover household income.

The data used in this study range from 1998 to 2020 and are derived from two major sources (Table 1). The dependent variable in the analysis is household income, and the major explanatory variable is rice price, with the proportion of the household's income earner(s) serving as a control variable. The household income is analyzed at five quintiles to assess the effect of rice prices at different income levels.

Table 1: Data Description

Variable	Description	Frequency	Period	Source
Rice price				
Rice Price	White rice 100% grade B	Monthly	1998–2019	Thai Rice Exporters Association
Agricultural household characteristics				
INC	Gross income	Biennially	1998–2019	Socio-Economic Survey, National Statistical Office
P_Earner	Proportion of household's income earner(s)	Biennially	1998–2020	Socio-Economic Survey, National Statistical Office

The model we used is the mixed data sampling (MIDAS) regression; for more information, see Ghysels et al. (2004, 2005, and 2006), Ghysels et al. (2007), and Ghysels (2018), among others. Precisely, the MIDAS regression is given by

$$Y_t = \alpha + \beta U_t + f\left(\left\{X^H_{\frac{t}{m}}\right\}, \theta, \lambda\right) + \varepsilon_t, \quad (1)$$

where Y_t is the biennial income at time t, α is the intercept, and U_t is a regressor with the same data frequency as Y_t, which can be also a lagged income and proportion earner in this case. $X^H_{\frac{t}{m}}$ is the set of monthly rice prices with m values for lower-frequency regressors at time t and t/m is a positional indicator of the higher-frequency data effect. β, λ, and θ are the parameters to be estimated, and *f(.)* in this study is assumed to be the weighting scheme function. This study used an unrestricted weighting scheme function as U-MIDAS, see Foroni et al. (2015). Finally, lambda (λ) can be used to represent a simple linear model. The empirical model is given by

$$INC_{t,q} = \alpha + \gamma INC_{t-1,q} + \beta_1 P\_Earner_{t,q} + \lambda f\left(\left\{\text{Rice Price}^H_{\frac{t}{m}}\right\}\right) + \varepsilon_t \quad (2)$$

where q is the quantile (0.20, 0.40, 0.60, 0.80, and 1.00).

Results

Table 2 shows the U-MIDAS regression results. The effect of rice price on rice farming household income is analyzed using the unrestricted weighting scheme function. We found that rice prices have a positive impact on income, but it is not all significant and varies by quantile. Households with income in the top and bottom quintiles are less likely to be affected by rice prices. Meanwhile, households with income ranging from the second to fourth quintiles can have welfare gain when the price rises. This means that the common perception may not be true because the higher price does not always lead to higher household income for all quantiles. Moreover, the lowest-income households can be the net consumer who is worse off from the rising price, whereas the highest-income households may have better

income from other source streams than rice farming. Note that the proportion of household income earners has a significantly positive effect but is not so strong and varies by quantile. This study's insights indicate that the advantage of rising price is not always positive for all households, especially for the lowest-income houses. Hence, the one-size-fits-all policy from government agencies will not be effective in this regard.

Table 2: Results of U-MIDAS regression for rice farming household's income

Variable	Rice farming household's income ($INC_{t,q}$)				
	q = 0.2	q = 0.4	q = 0.6	q = 0.8	q = 1.0
Model (1)					
Rice Price^{H}	0.07**	0.21**	0.32**	0.43***	0.35
	(0.02)	(0.08)	(0.10)	(0.10)	(8,242.00)
Constant	1118.00***	2538.00**	4377.00***	8005.00***	30210.00***
	(281.10)	(1,035.00)	(539.30)	(7,453.00)	(7,453.00)
Model (2)					
Rice Price^{H}	0.03	0.12***	0.30**	0.47***	0.43**
	(0.03)	(0.02)	(0.09)	(0.09)	(0.13)
$P\_Earner_{t,q}$	8160.00*	37620.00***	59560.00***	9,265.00	353700.00***
	(3,808.00)	(3,207.00)	(7,407.00)	(17,120.00)	(66,060.00)
Constant	−4273.00	−22250.00***	−35760.00***	1049.00	−214600.00***
	(2,511.00)	(2,101.00)	(4,185.00)	(13,500.00)	(46,230.00)
Model (3)					
Rice Price^{H}	0.05*	0.12***	0.20***	0.31***	0.37
	(0.02)	(0.02)	(0.04)	(0.07)	(0.61)
$INC_{t-1,q}$	0.48***	0.57***	0.57***	0.53***	0.35
	(0.06)	(0.09)	(0.09)	(0.13)	(0.44)
Constant	518.79	880.81	1,308.00	2620.00	18,170.00
	(331.08)	(646.81)	(1,136.00)	(2,457.00)	(17,890.00)
Model (4)					
Rice Price^{H}	0.03**	0.11***	0.20**	0.36***	0.41*
	(0.01)	(0.02)	(0.06)	(0.04)	(0.17)
$INC_{t-1,q}$	0.25**	0.16	0.46*	0.54***	−0.2
	(0.08)	(0.25)	(0.21)	(0.08)	(0.33)
$P\_Earner_{t,q}$	5830.00**	31170.00*	47390.00**	10,960.00	406300.00**
	(1,938.00)	(0.16)	(10,370.00)	(5,867.00)	(8,972.00)
Constant	−3083.00*	−18470.00*	−29940.00**	−5,776.00	−243,900
	(1,256.00)	(8,194.00)	(8,160.00)	(4,161.00)	(6,053.00)

Notes: ***, **, * represent 1%, 5%, and 10% levels of significance, respectively. Standard errors are reported in parenthesis. Source: Calculated by the authors

Conclusion

The higher price typically leads to higher income. This is obvious from a standard economic theory of how rice price affects the rice farming household's income, but this effect has rarely been discovered quantitatively. Hence, this study aims to disclose this effect, employing the U-MIDAS regression to handle the different-frequency mismatches between the price and income. The results show that the positive effect of rice price on farmers'

household income is weak and varies by quantile. This may not always be the case in Thailand. Farmers with middle-income levels are the only ones who benefit from price increases. The higher proportion of household earners also contributes to the welfare gain. Hence, using rice prices as a political tool can be ineffective and useless, especially when the target population is the lowest-income households. This also means any policies and measures that support higher rise prices are likely to benefit higher-income households except for the highest ones.

Acknowledgments

We thank seminar participants at the RIN workshop for their feedback. We are also grateful to IDE-JETRO for their time and effort to organize the workshop.

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