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## The Impact of COVID-19 on household income in Thailand

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### Introduction

Since March 2020, the COVID-19 pandemic has grabbed policy attention of governments around the world. To contain the spread of the virus, the Thai government imposed a lockdown, first in Bangkok on March 18, 2020 and then nationwide on March 26, 2020. This was followed by a curfew on April 3, 2020. The lockdowns were eased gradually from May 2020 and the curfew was revoked on June 15, 2020.

The swift actions taken by the Thai government were successful in controlling the first wave of COVID-19 pandemic in 2020. However, this success came with immense economic costs. The mobility restrictions imposed at national and international levels depressed the tourism sector, which is one of the key economic sectors in Thailand. Private consumption of durable goods declined sharply. About 8.4 million people, especially in manufacturing and service sectors faced the risk of losing their jobs, and people who relied on remittances and informal sector jobs saw a decline in their income (World Bank Group, 2020).

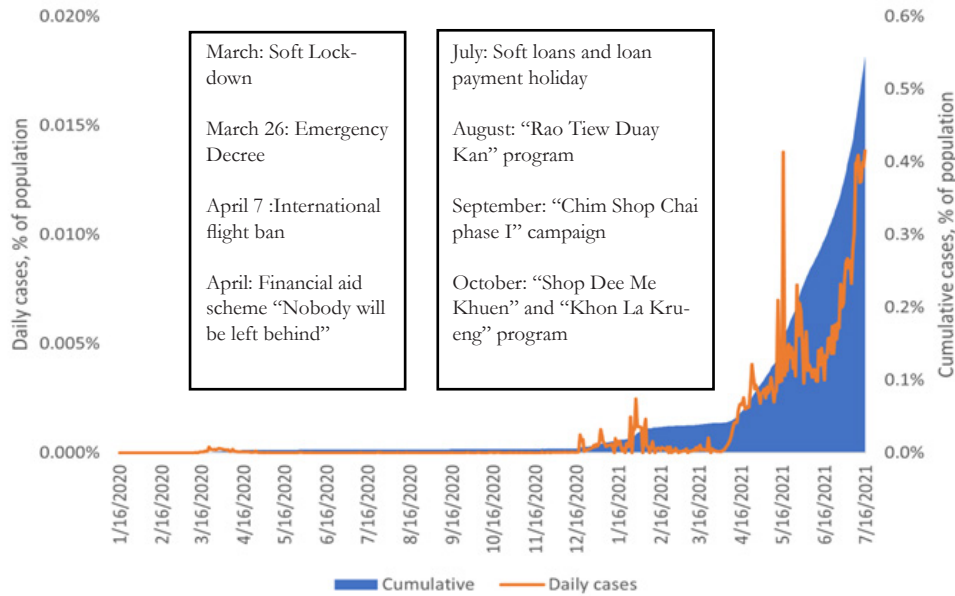
To respond to the negative economic shock from its response to the pandemic, the Thai government implemented various policy measures including soft loans, cash handouts, and tax refunds. At the scale of the population, the net impact of these policies in countering the effects of the COVID shock is not well understood. In this Brief, we fill this gap in our understanding of the impact of the COVID shock on Thai people's income and livelihood strategies. We use two rounds of phone survey data repre-

### Key Facts

- Thai households saw a significant decline in household income in the first 12 months after the pandemic.
- Compared to March 2020 (pre-COVID), household incomes dropped by 14% in July 2020, recovered some but remained 4% lower in September 2020.
- Almost a year into the crisis, incomes were 6% lower in February 2021 compared to March 2020.
- Impacts were widespread geographically and by household characteristics.
- In designing policy responses, decision makers should account for these broad effects of a shock across locations and household characteristics.

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Figure 1: Confirmed COVID-19 daily and cumulative cases, government policy responses, and timing of survey data collection



Source: <https://ourworldindata.org/coronavirus/country/thailand>

sentative at national and rural/urban levels, conducted in October and November 2020 (Round 1) and in March and April 2021 (Round 2) to investigate following research questions: (1) What impact did the COVID shock have on household income in the first 12 months after the onset of the pandemic in March 2020? and (2) Were these effects different for households residing in rural vs. urban areas, tourist vs. secondary provinces, and by other household characteristics?

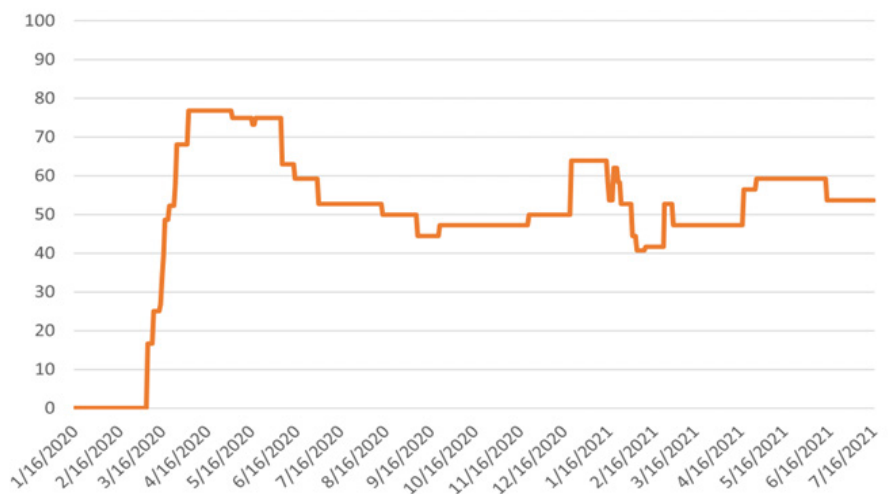
### Brief overview of pandemic situation and government responses

The first domestic case of COVID infection in Thailand was announced on January 26, 2020. The number of new cases remained below 40 per day until mid-March 2020 when they jumped to 100 cases per day (Figure 1). The first wave of disease outbreak started in mid-March and ended in late April 2020.

Around this time, Thai government responded with several measures to mitigate the spread of the contagion. For example, in late January 2020, the Department of Disease Control (DDC) mandated social distancing and mask-wearing and promoted hand washing practices. Soft lockdowns were

imposed on March 18 at varying levels of enforcement across the country. On March 26, the government invoked the "Emergency Decree" across Thailand and expanded COVID testing and quarantine facilities. The government also implemented Thai Chana Application for contact tracing at public places. The curfew was imposed and became effective on April 3. Lastly, the government suspended all commercial international flights from April 7. These different measures are summarized in a Stringency Index, which peaked between March and early June as shown in Figure 2.

Figure 2. Stringency Index



Source: <https://ourworldindata.org/coronavirus/country/thailand>

Table 1. Respondent and household characteristics (Round 1 and Round 2)

Characteristics	Round 1 (N=800)		Round 2 (N=800)		p-value
	mean	sd	mean	sd	
1=Resides in urban area	0.51	0.50	0.51	0.50	1.000
1=Resides in a tourist province	0.47	0.50	0.48	0.50	0.689
Minutes to travel to a nearest town in wet season	32.11	91.35	31.00	128.92	0.843
Respondent age	43.57	12.09	44.08	12.47	0.406
Gender of Respondent (1=male)	0.31	0.46	0.33	0.47	0.390
Respondent education (# of years)	10.03	4.79	9.78	4.68	0.291
Household size	3.93	1.84	3.75	1.92	0.056
Age of household head	50.92	12.20	50.71	12.18	0.491
Gender of household head (1=male)	0.61	0.49	0.60	0.49	0.683
Education of household head (# of years)	7.69	4.03	8.25	4.44	0.005

Source: Phone surveys Round 1 (October-November 2020) and Round 2 (February-March 2021).

Through these different measures, the Thai government was successful in averting the public health crisis, with the public health threat well contained after mid-June. With impressively low rates of infection and community transmission, curfew was revoked in June and lockdowns were gradually phased out by July 1. This is reflected in the declining trend in the Stringency Index from June 2020. However, restrictive measures were not completely eliminated and the Stringency Index remained above the pre-COVID levels for a significant period of time (Figure 2). With the second and third waves of rising infections, there was a slight jump in the Stringency Index around December 2020 and April-May 2021.

The impacts of pandemic restrictions were predicted to slow the Thai economy and generate widespread income losses, impacting both urban and rural households (World Bank Group, 2020). After the first wave of COVID outbreak, more than 11 million workers were estimated to suffer lost income and employment, especially workers from manufacturing, tourism, and service sectors (Krungsri research, 2021). About half of Thai companies were facing liquidity shortages. The number of people who lived below USD 5.5 per day (in purchasing power parity, PPP) was expected to double from 4.7 million in the first quarter of 2020 to 9.7 million in the second quarter of 2020.

Next, we examine the extent to which people experienced these predicted losses in income post-COVID. Using sur-

vey data, we estimate the income effect of COVID shock over three time frames—4 months, 6 months, and 11 months after the pandemic began in March 2020.

## Methods

Two rounds of representative phone surveys were conducted between October and November 2020 (Round 1) and February and March 2021 (Round 2). These surveys were conducted by GeoPoll, a survey platform used by Mobile Accord, Inc., a company that specializes in survey research via mobile phone across the globe.

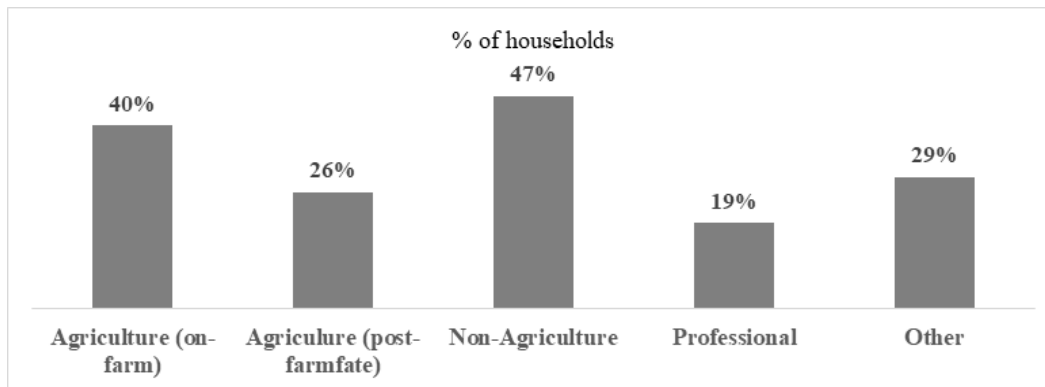
In each Round, 800 respondents, stratified 50/50 by rural and urban locations were selected based on a simple random sampling (SRS) technique from GeoPoll's verified list of 100,000 mobile subscribers in Thailand. The survey was targeted to the main shopper of the household who was at least 18 years old. Income data were collected for March and July 2020 in Round 1, and for March 2020, September 2020 and February 2021 in Round 2. In both the rounds, income data for March 2020 are considered baseline estimates of income prior to the COVID shock.

## Results

Table 1 shows respondent and household characteristics of the sample from the two survey rounds. The average age of respondents in both rounds is 44 years old. The sampled respondents are mostly women. The share of male respondents is 31% in Round 1 and 33% in Round 2. Number of years of education for respondents



Figure 3 Sources of income reported for March 2020 (pre-COVID) by respondents sampled in Round 1



Source: Phone survey Round 1 (October-November 2020)

is not statistically different in the two rounds. Average household size is approximately 3.8 in Round 2, which is slightly lower than 3.9 in Round 1. On average, the household head is 51 years of age and male (60%). The average number of years of education of the household head is 7.7 years in Round 1 vs. 8.2 in Round 2. This difference is statistically significant at  $p=0.005$ . Except for the household size and the education of household head, the cross-sectional samples from the two rounds of survey are not statistically significantly different in respondent and household characteristics.

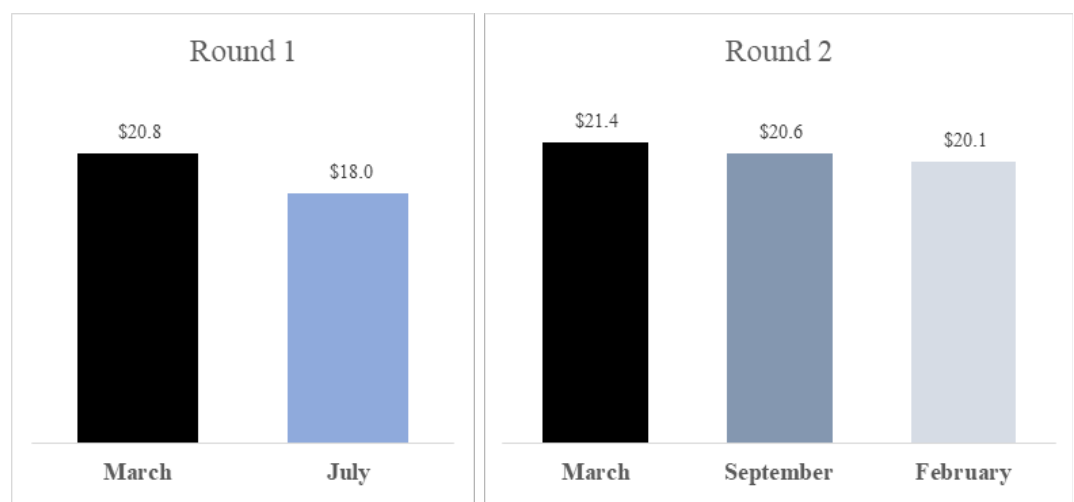
Figure 3 shows March 2020 (pre-COVID) sources of income reported by households surveyed in Round 1. Income from non-agriculture sector was the most important source, reported by 47% of households, followed by on-farm agriculture income (40%). Post-farmgate sector (e.g., processing, marketing, trading farm derived products) was reported as the source of income by 26% of households. About 19% of households reported having professional employment income, and 29% had income from other sources (including remittance, retirement income, etc.).

The average per capita per day income in PPP\$ in March 2020 (pre-COVID) and over the first 12 months

after the start of the COVID crisis are presented in Figure 4. On average, per capita per day income in March 2020 (pre-COVID) was about \$21. It dropped to \$17 four months into the crisis (i.e., July 2020), but was almost at the pre-COVID level by September 2020, before sliding back a little in February 2021.

Next, we address the question about the impact of the COVID shock on household income by estimating changes in the household income in the months of July, September, and February relative to March. Simply comparing the mean incomes reported in Figure 4 may not give an accurate assessment because the effects could be confounded by unobservable characteristics of our sampled households. Thus, we use panel data methods to control for potentially endogenous unobservable factors.

Figure 4 Average per capita per day income in PPP\$ by survey Round 1 (March and July 2020) and survey Round 2 (March 2020, September 2020, and February 2021)



Source: Phone surveys Round 1 (October-November 2020) and Round 2 (February-March 2021). Estimates are based on panel households with income data reported in both the months--March and July in Round 1 ( $N=717$ ) and in all three months--March, September, and February in Round 2 ( $N=749$ ).

Table 2. Change in per capita per day total HH income (2018 PPP\$) from March 2020 (pre-COVID) to July 2020, September 2020, and February 2021, fixed effects model estimates for total population

	July 2020	September 2020	February 2021
Month (base category =March)	-2.824***	-0.773*	-1.313***
	(0.576)	(0.399)	(0.388)
Observations	1434	1498	1498
R-squared	0.073	0.015	0.034
Number of Households	717	749	749
Dep var. mean (in March)	20.82	21.37	21.37
Percent effect	-13.57%	-3.62%	-6.15%

Notes: Robust standard errors (clustered at household level) in parentheses. All models include sample weights to adjust for following population level characteristics—rural/urban split, household size, household head's education and gender. Income effects for July are based on survey data from Round 1 and for September and February, they are based on survey data from Round 2. Only panel households with income data in both the comparative months are included. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ .

We estimate three household fixed effects models by regressing household income in March 2020 and one of the post-COVID months—July, September and February—on the month variable which was equal to zero if observation was for March and equal to 1 if the observation was for the post-COVID month. The income effects of the COVID shock for July 2020 are based on Round 1 data, and for September 2020 and February 2021 they are based on Round 2 data. For all three months/models, the income effect is relative to the household income in March 2020, which represents the pre-COVID baseline month. Results for the overall sample are presented in Table 2, and by sub-groups based on location and household characteristics in Table 3.

Three main results stand out from this analysis. First, households in Thailand experienced a significant decline in income over the 12 months since the start of the pandemic in March 2020 (Table 2). The decline in income was steepest (\$2.8 per capita per day or 13.6%) in the first four months between March and July 2020. Per capita per day household incomes in September 2020 increased some relative to July but remained 3.6% below (or \$0.77 less than) the levels in March 2020. Almost 12 months into the crisis, per capita per day household income in February 2021 were still \$1.31 (or 6.2%) below the pre-pandemic levels in March 2020.

Second, the macro-level COVID shock had differential impact on household income by whether the household

also experienced a micro-level shock of having done stay-at-home (Table 3). The COVID effect on household income was higher among households where a member had done stay-at-home compared to households where no one had done stay-at-home. However, this effect is statistically significant only in the first period of analysis (i.e., in July). In this initial period, households that did stay-at-home experienced a 16.7% drop in income compared to a drop of only 2% drop amongst households that had not done 'stay-at-home'.

Third, in the initial few months when the restrictions were most stringent, the income effects were widespread over several location and household characteristics. Our subgroup analysis shows that the income effects are not statistically significantly different by urban and rural areas and household characteristics such as gender and education of the household head (Table 3). Incomes improved in September and February for households in tourist provinces and in rural areas relative to their counterparts. The improvement in income was significantly more in tourist provinces in September compared to secondary provinces. However, with the exception of this one case, the difference between the different sub-groups remained statistically insignificant in all three post-COVID months, suggesting broad impacts across the country and household types.

Table 3. Change in per capita per day total household income (2018 PPP\$) from March (pre-COVID) to July 2020, September 2020, and February 2021, by whether someone in the household had done 'stay-at-home', and by location and household characteristics

	July-2020		September-2020		February-2021	
	Household has done 'stay-at-home'					
	No	Yes	No	Yes	No	Yes
Month (base category=March)	-0.5	-3.369***	-0.29	-0.948*	-0.434	-1.632***
	-0.559	-0.86	-0.708	-0.485	-1.068	-0.368
Percent effect	-2.14%	-16.66%	-1.36%	-4.45%	-2.03%	7.65%
Observations	256	1178	392	1106	392	1106
P-values	0.005		0.443		0.289	
	Tourist provinces					
	No	Yes	No	Yes	No	Yes
Month (base category=March)	-2.294**	-3.422***	-1.413***	-0.0229	-1.384**	-1.230**
	-0.996	-1.012	-0.442	-0.648	-0.538	-0.559
Percent effect	-12.34%	-14.67%	-7.31%	-0.10%	-7.16%	-5.18%
Observations	784	650	820	678	820	678
P-values	0.427		0.077		0.843	
	Urban					
	No	Yes	No	Yes	No	Yes
Month (base category=March)	-2.137***	-3.497***	-0.917*	-0.625**	-1.023	-1.611***
	-0.63	-1.26	-0.482	-0.324	-0.629	-0.453
Percent effect	-13.83%	-13.41%	-5.02%	-2.54%	-5.60%	-6.56%
Observations	708	726	736	762	736	762
P-values	0.335		0.714		0.449	
	Gender of household head					
	Female	Male	Female	Male	Female	Male
Month (base category=March)	-3.653**	-2.286***	-1.181*	-0.505	-1.473*	-1.208***
	-1.608	-0.532	-0.649	-0.492	-0.801	-0.369
Percent effect	-17.18%	-11.13%	-4.88%	-2.59%	-6.09%	-6.19%
Observations	554	880	692	806	692	806
P-values	0.420		0.407		0.764	
	Education of household head is below the country's median level					
	Yes	No	Yes	No	Yes	No
Month (base category=March)	-2.830***	-2.772***	-0.692	-1.224**	-1.250***	-1.661***
	-0.795	-0.873	-0.46	-0.501	-0.449	-0.514
Percent effect	-15.01%	-7.64%	-3.61%	-3.66%	-6.51%	-4.97%
Observations	622	812	688	810	688	810
P-values	0.961		0.434		0.547	

Notes: Robust standard errors in parentheses. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ . P-values are for sub-sample equality test (for month coeff.). All models include sample weights to adjust for following population level characteristics—rural/urban split, household size, household head's education and gender. Data for July are from Round 1, and for September and February are from Round 2.

## Conclusion and policy implications

Soon after the coronavirus disease 2019 was declared a pandemic by the World Health Organization in March 2020, governments around the world reacted rapidly and introduced public health measures restricting the social and economic behavior of people to suppress the virus. Thailand was no exception to this and implemented both macro level containment and mitigation measures such as lockdowns and curfews, and community level interventions that emphasized behavior change by individuals and encouraging people to use safety measures such as self-quarantine, social distancing, and hand washing. These measures are a potent tool for curbing the spread of COVID-19 but have social and economic costs.

Using two rounds of representative surveys from Thailand, we quantified one of these costs—i.e., the impact of a macro-level shock on household income. We focused on the first 12 months of the COVID shock. Results suggest that Thai households experienced a significant negative impact of COVID-19 on their income levels. In the immediate few months after the COVID shock, household incomes dropped 14%. Some of these losses were regained over the next few months as COVID restrictions were lifted. The income gains were much higher in primary tourist provinces compared to secondary provinces. However, with the onset of a second wave in late 2020, some of the restrictions were reinstated. As a result, 12 months after the crisis began, household incomes in Thailand were still 6% below the pre-COVID levels.

The lingering effects of the COVID shock over time suggest the need for continued support of social protection programs. We also found that the COVID shock affected rural and urban areas similarly and that the effects were comparable across different types of households. These results are consistent with the findings from similar surveys conducted in five African countries (Maredia et al. 2022). The pervasiveness of the effects of a macro-level shock supports the growing evidence of interconnectedness of people and communities across geographies through factor and product markets. An implication of this finding is that, in designing policy responses and relief measures, decision makers should account for these broad effects of a shock that cut across locations, and household characteristics.

Since tourism contributes to a significant share of national GDP of Thailand, we examined differential effects of the COVID shock by primary and secondary tourist provinces. Our results suggest that in the initial phase when restrictions were most stringent, the effects of the pandemic were severe in tourist provinces as well as in secondary provinces. However, incomes bounced back more rapidly in the tourist provinces after the restrictions were lifted compared to secondary provinces. Thus, more policy attention is needed to assist secondary tourist provinces to bounce back from lost jobs and incomes due to the COVID crisis.

## References

- Datareportal. (2020). Digital 2020: Thailand. Available at: <https://datareportal.com/reports/digital-2020-thailand>
- Krungsri research. (2021). Covid-19 crisis: The impact on business and choice of policy tools. Research Intelligence, Krungsri research. Available at: <https://www.krungsri.com/en/research/research-intelligence/ri-covid19-crisis-en>
- Maredia, M.K., Adenikinju, A., Belton, B., Chapoto, A., Faye, N.F., Liverpool-Tasie, S., Olwande, J., Reardon, T., Theriault, V., and Tschirley, D. (2022) COVID-19's impacts on incomes in urban and rural areas are surprisingly similar: Evidence from five African countries. *Global Food Security*, Volume 33, June 2022, 100633. <https://doi.org/10.1016/j.gfs.2022.100633>.
- National Statistical Office (2019) Demography population and housing branch. Available at: <http://statbi.nso.go.th/staticreport/page/sector/th/01.aspx>
- Office of the National Economic and Social Development Council (2020) Statistics of social development. <https://www.nesdc.go.th/main.php?filename=social> [in Thai]
- World Bank Group. (2020). Thailand Economic Monitor: Thailand in the Time of COVID-19. World Bank, Bangkok. Available at: <https://www.worldbank.org/en/news/press-release/2020/06/30/major-impact-from-covid-19-to-thailands-economy-vulnerable-households-firms-report>



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