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Urban food prices under lockdown

Evidence from Myanmar’s traditional food retail sector during COVID-19

Joseph Goeb, Mywish K. Maredia, Khin Zin Win, Ian Masias, Isabel Lambrecht, Duncan Boughton, and Bart Minten

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ABSTRACT

Many governments imposed stringent lockdowns during the COVID-19 pandemic as a public health measure to suppress the spread of the disease. With consumer incomes already depressed, the potential impacts of these measures on urban food prices are of particular concern. This working paper examines the changes in Myanmar's urban food prices during lockdown using detailed food price data collected from a panel of phone surveys conducted in August and September 2020 of 431 family-owned retail shops in Myanmar's two largest cities, Yangon and Mandalay. We find that the supply side of Myanmar's food retail sector was largely resilient to the shocks and lockdowns throughout the first six months of the COVID-19 pandemic. Estimates from a fixed effects difference-in-differences model reveal that food prices were 3 percent higher in townships under lockdown compared to those not under lockdown, a statistically significant but modest effect. Lockdowns had smaller effects on prices for highly processed food items sourced directly from companies, but larger effects on prices for raw or lightly processed commodities sourced through wholesale markets, which comprise a larger share of urban consumer's diets. Retailer margins did not change significantly under lockdown restrictions, suggesting no evidence of price gouging. Overall, our findings of a modest impact of the lockdown on urban food prices underscore the importance of keeping the food supply chain–including wholesale markets and retail shops–functioning as completely and as safely as possible during times of crisis, as was mostly the case early in the crisis for the two cities in this study.

1. INTRODUCTION

Rapid policy responses and public health measures were necessary to control the spread of COVID-19 for which there was no therapeutic drug (Wu et al. 2020) or vaccine when it was declared a pandemic in March 2020. Where the risks of spread were largest, many governments imposed stringent lockdowns, or stay-at-home orders, to limit movement and human interactions. These measures can curb the spread of COVID-19 (Kraemer et al. 2020; Nussbaumer-Streit et al. 2020; Jefferson et al. 2008; Aiello and Larson 2002) but have social and economic costs, such as lost employment and incomes (Baek et al. 2020; Egger et al. 2021; Maredia et al. 2021) as well as increased poverty (Laborde et al. 2020; Mahler et al. 2020; Lakner et al. 2020; Summer et al. 2020), and contributed to overall economic contraction (IMF 2020).

Urban food systems are of particular concern in such a crisis because of anticipated disruptions to food supply chains (Carducci et al. 2021; Nguyen et al. 2020; Cullen 2020; Devereux, Béné, and Hoddinott 2020; Reardon et al. 2020). For urban consumers, who rely on markets for most of their food consumption, the crisis has had adverse impacts on food availability, food security, and diet quality (Adjognon et al. 2021; Hirvonen et al. 2021). Equally important are the impacts of COVID-19 policies on food prices, which can provide a more accurate assessment of food scarcity than other measures (Weinberg and Bakker 2014). Food price changes can disproportionately impact the poor, as they often pay higher prices (Chung and Myers 1999) and spend a higher proportion of their incomes on food (Easterly and Fischer 2001; Wodon and Zaman 2008). Overall, increases in food costs can push more vulnerable households into poverty and hunger (Gustafson 2013).

The empirical evidence of the effects of COVID-19 lockdowns on food prices is limited and inconclusive. Some studies provide evidence of relatively minor effects of such disasters on product prices (Gagnon and Lopez-Salido 2020) and of COVID-19 induced effects on online retail food prices in India (Mahajan and Tomar 2020) and rice prices in Myanmar (Goeb et al. 2021). Yet, other recent studies show larger and more nuanced changes in food prices. For example, research in Ethiopia shows large vegetable price increases (Hirvonen et al. 2021b), while evidence from China and India shows large price changes for fresh vegetables but small changes for non-perishable grains (Ruan et al. 2021; Yu et al. 2020; Varshney et al. 2020; Narayana and Saha 2020).

This article contributes to the growing, but still sparse literature on the effects of COVID-19 lockdowns on food prices. Specifically, we examine the changes in urban food prices during lockdown in Myanmar's two largest cities, Yangon and Mandalay, using detailed food price data from 431 family-owned retail shops. Such traditional retail shops play a large role in the 'last mile' of food delivery to consumers in many developing countries. In Myanmar, specifically, about 85 percent of all consumer goods and about 90 percent of all foods are sold through the traditional retail sector (King 2020; USDA 2018). Through a panel phone survey in Myanmar, we collected detailed price data for specific food products typically sold by these small retail outlets–perishable foods (eggs and onions), shelf-stable staples (rice and chickpea), and highly processed foods (cooking oil, powder milk, dry noodles, coffee mix, and soda).

We assess price changes from March 2020 (pre-pandemic) to September 2020, six months into the pandemic and shortly after lockdown measures were implemented in many urban townships. Using a shop-level fixed effects difference-in-difference (DiD) model, we estimate the impact of the lockdowns on three price-related variables at the retail level–procurement (buying) prices, consumer (selling) prices, and retail margins (the difference between the two prices). Changes in the retail margins can provide two insights: how much of the shock is absorbed by small retailers themselves instead of being passed on to final consumers; and whether there is any evidence of price gouging, which often follows major disasters and supply or demand shocks (Beatty et al. 2021).[1]

Our analysis provides three main results. First, the supply-side of the urban food retail sector in Myanmar proved to be largely resilient to shocks in the first six months of the COVID-19 pandemic as evidenced by the lack of substantial price increases or disruptions in supply chains. We find that even during widespread lockdowns, 90 percent of the products surveyed were sourced from their usual suppliers. Further, the food price effects, though statistically significant, were modest in magnitude, increasing by only 3 percent overall in lockdown townships.

Second, the price effects of lockdowns varied across types of suppliers and shop characteristics. The lockdown had smaller effects on prices for processed, packaged, and branded food items that are sourced directly from companies, but larger effects for raw or lightly processed commodities that are sourced through wholesale markets (e.g., rice, eggs, and onions). The latter category of foods comprises a larger share of urban consumers' diets (Goeb et al. 2021), and this result highlights the importance of keeping wholesale market channels operating safely during times of crisis or shocks.

Importantly, we find that townships with greater proportions of vulnerable residents had similar price increases as those with smaller shares of vulnerable people. Any food price increases will have greater relative effects on vulnerable households with lower incomes, but the fact that shops in more vulnerable townships do not show larger price increases during lockdown is an encouraging result. Additional results show that products in shops farther from production zones had larger price increases. Larger shops, which may have more formalized and stronger relationships with suppliers, show smaller price effects from the lockdowns. On the other hand, retailers with more food retailers located nearby had larger price increases, perhaps reflecting changes in demand.

Third, retail margins did not change significantly due to the COVID-19 crises and lockdown restrictions. This indicates two things: the modest increase in buying prices that we observed were fully passed on to the consumers and not absorbed by the retailers; and there is no evidence of price gouging for these traditional retail shops, consistent with evidence from India (Mahajan and Tobar 2020) and the United States (Malone et al. 2020). Price gouging during the pandemic has been observed in other contexts unrelated to food, e.g., masks and hand sanitizer (Cabral and Xu 2020), but reputational concerns can reduce the risks of price gouging emerging (Akerlof 1980, Mahajan, and Tobar 2020). In the case of traditional urban food retail in Myanmar, the competitiveness of the food retail market and the implied low market power of each shop, along with the related fear of losing customers to other nearby shops, could have inhibited price gouging behavior in our sample.

Our study adds to the general literature on the impact of disasters on disruptions in food availability and prices (e.g., Cavallo, Cavallo, and Rigobon 2014; Heinen, Khadan, and Strobl 2019; Gagnon and Lopez-Salido 2020), and more specifically to the literature that assesses the price effects of the ongoing COVID-19 pandemic (e.g., Mahajan and Tobar 2020; Ruan et al. 2021; Rude 2020; Narayanan and Saha 2020; Yu et al. 2020). Compared to the existing pandemic literature, our study has three main advantages and innovations. First, unlike other studies that relied on secondary data, we use primary data from phone surveys dedicated to understanding the impact of COVID-19 on retail food prices. This allows us to explore the effects of lockdowns on three types of price variables at the shop level–buying price, (i.e., procurement), selling price (i.e., consumer facing), and margins, which is rare in the literature. Second, we focus on the traditional food retail sector, which is an important channel for the delivery of a wide range of food to urban consumers. Thus, we can focus specifically on the effects of the crisis on urban small retail enterprises and consumers. Third, we provide evidence of COVID-19's effects on food prices by utilizing product specific data that

[1] We follow Beatty et al. (2021) and define price gouging as an abnormal increase in margins above input prices, after controlling for seasonality and longer-run trends.

controls for quality and branding of most products, thus reducing the noise around price data and enabling more accurate comparisons across time and across shops.

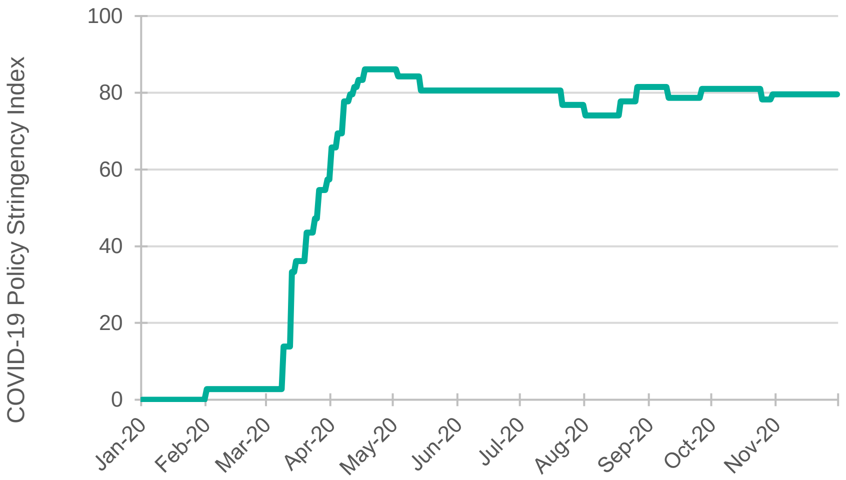
This paper proceeds with background information on Myanmar's COVID-19 policy response and urban food consumption in Section 2. Section 3 describes the sample and the food price data. Section 4 lays out the shop fixed effect difference-in-differences model and discusses extensions to test for heterogeneous effects across shop covariates. Our results are presented in Section 5, and Section 6 discusses the implications of those results and offers conclusions.

2. BACKGROUND

2.1. Myanmar's COVID-19 policy response and impact

Myanmar experienced two waves of COVID-19 infections and response measures in 2020, the onsets of which can be roughly tied to the months of March and August. In early February 2020, the Government of Myanmar was quick to respond to COVID-19 and began implementing safety measures. The initial policies were modest–restricting visas and arrivals from China. This is shown in Figure 1 as the first small increase from zero in the University of Oxford's COVID-19 stringency index, a metric designed to track the severity of movement restrictions imposed during the crisis. In late March, the policy response became more stringent and restricted people's movements and gatherings. The policy stringency index peaked in April (to 86 points on a scale of 0-100), when the first COVID-19 cases were confirmed in Myanmar and strict lockdowns were implemented in densely populated townships in Yangon, the commercial capital. These lockdown measures required that individuals only leave their dwellings for essential food shopping and to travel to jobs in a limited number of essential sectors.

Figure 1. COVID-19 policy stringency index, Myanmar January 1–November 30, 2020



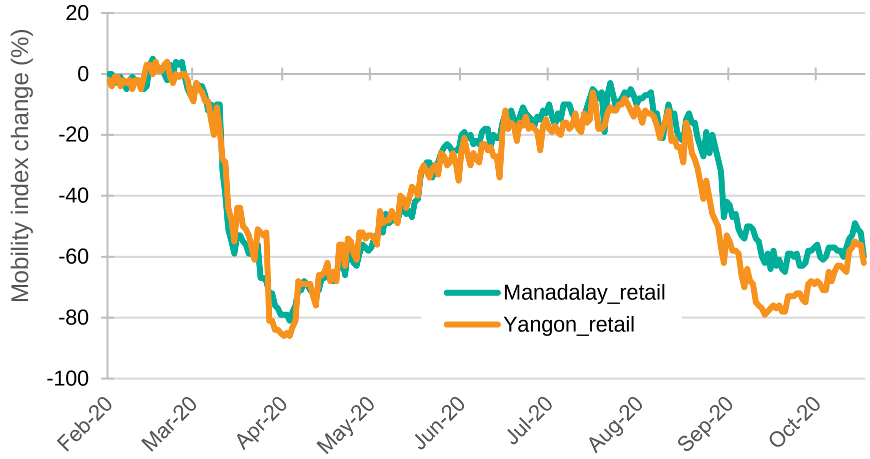
Source: University of Oxford COVID-19 Government Response Tracker.
Note: 100 is the strictest response representing nationwide restrictions across 9 indicators including school and workplace closures and lockdowns.

The number of confirmed COVID-19 infections during Myanmar's first wave were limited. The strictest lockdowns were lifted in mid-May 2020, but widespread limitations on transportation and gatherings continued, including a ban on international commercial passenger flights, closures of most schools, restrictions on intranational travel and trade, and partial closures of land borders to neighboring countries (Goeb et al. 2020a). By early August, the average number of confirmed new cases per day was less than ten. Consequently, the government further eased restrictions on mass gatherings (Deshpande et al. 2020). Unfortunately, the relaxations were short-lived, and a second wave quickly took hold in mid-August, spreading more quickly and widely than the first wave. Myanmar's major urban areas were particularly hard hit (Deshpande et al. 2020).

The Myanmar government again announced curfews and lockdown measures in Yangon on September 20 and quickly extended them to Mandalay, Myanmar's second largest city. These restrictions were administered at the township level[2] within each city (Arnold et al. 2015). During the pandemic, the Myanmar government established COVID-19 response committees in each township's General Administration Department (GAD) as the responsible body to manage and oversee policies. The response committees' responsibilities included overseeing lockdowns and curfew measures (MIMU 2020), though in practice, the lockdowns were not uniformly enforced by the GADs. In some townships where lockdowns were announced, people and traffic could move largely uninhibited as if there were no major restrictions, while in other townships local officials strictly implemented transportation restrictions, sometimes blockading major roads at township borders. Thus, application and enforcement of COVID-19 restrictions were inconsistent across townships, even in the same city.

Despite inconsistent implementation, the effects of Myanmar's policy responses to each wave of COVID-19 were substantial. Google's retail mobility index–which tracks trends in peoples' mobility, relative to a January/February 2020 baseline–in Mandalay and Yangon shows successive waves of overall reduced mobility over the period January to October 2020 (Figure 2). Mobility declined as the first measures to control the pandemic took hold in April 2020 and then declined again as the second wave of the pandemic became more pronounced in September/October 2020. The effects during the second wave were slightly more pronounced in Yangon than in Mandalay.

Figure 2: Google™ index of retail mobility in Yangon and Mandalay



Source: Google™ mobility data.

Overall, Myanmar's economic growth declined from 7 percent in FY 2019 to 2 percent in FY 2020 (World Bank, 2020). Diao et al. (2020) estimated that the April lockdown shrunk Myanmar's economic output by 40 percent and led to approximately 5 million people losing employment. The lockdown measures imposed during the second wave led to an alarming increase in income-based poverty from 41 percent in August 2020 to 62 percent in October 2020 (Headey et al., 2020), and an increase in moderate to severe food insecurity increasing from 12 percent to 25 percent over the same period (World Bank, 2020). Myanmar's agri-food system was also not immune to the shocks, though many sectors were resilient early in the crisis (Boughton et al. 2021).

[2] There are 33 townships in Yangon and 7 in Mandalay. The townships vary in population and geographical size. Mandalay's townships are relatively more populated than Yangon's, with an average population of 193,000 and 140,000 people per township, respectively. However, densities are higher in Yangon with 5,400 people per square kilometer compared to just 1,500 in Mandalay (MIMU 2019).

2.2. Urban diets, traditional retailers, and COVID-19 impacts

Rapid economic growth and urbanization in many Asian countries has led to a shift away from staples (e.g., cereals and tubers) to more animal-sourced proteins (e.g., meat, eggs, and fish), fruits, vegetables, and fats and oils (Pingali 2007). Consumption of processed foods has also increased, especially in urban areas (Reardon et al. 2014). Myanmar is experiencing a similar transformation as consumer preferences have shifted towards animal-sourced foods, fruits, vegetables, and processed and ultra-processed foods (which undergo major transformations and contain additives like coloring or sugar), as well as prepared snacks (Downs et al. 2018). Traditional retail shops in Myanmar sell a wide variety of food products, including at least some food items in each of these increasingly important categories.

Over the course of a week, 98 percent or more of urban households consume rice, onions, vegetable oil, and ultra-processed foods–items commonly sold at traditional retail outlets.[3] Eggs, the most common animal-sourced food sold by the traditional retail shops and a growing source of protein in Myanmar (Belton et al. 2020), are consumed by 78 percent of urban households. Overall, the food items sold at traditional retail outlets covered in this study comprise an important part of urban consumers' diets. Thus, any disruptions to the traditional retail sector caused by COVID-19 that cause changes in the prices for these food items will have meaningful impacts on the welfare and diets of urban consumers.

Lockdowns and mobility restrictions could present major obstacles to the food marketing system through shifts in demand or supply. In general, it is harder to move across townships where lockdowns are enforced. Higher delivery costs might put upward pressure on supply prices, while movement restrictions could either increase or decrease demand. The directions and magnitudes of shifts could vary across township and shop characteristics. With these complex forces acting on supply and demand in locale-specific ways, the effect of lockdowns on food prices is an empirical question best answered by exploring observed changes.

3. DATA AND SAMPLE DESCRIPTIVES

Our data for analysis come from telephone interviews conducted with 431 small family-owned retail stores in the two largest urban centers in Myanmar: Yangon and Mandalay. We randomly selected our sample from a listing of 693 traditional retail shops that derive at least 30 percent of their revenues from food product sales. This list was provided by "mom&pop", a Myanmar-based business intelligence company. The traditional retail sector in Myanmar is understudied, so there are no official estimates of the number of shops. We estimate that there are at least 2,000 in Yangon and 800 in Mandalay. We stratified our sample by townships within each city to ensure a wide geographic coverage and randomly selected shops within each township. The sample includes shops from 30 of the 33 townships in Yangon and all 7 townships in Mandalay.

This study uses data from two survey rounds conducted in August and late September, respectively. The latter captured data during the second much larger wave of COVID-19 and the subsequent lockdowns in Myanmar. The analysis in this paper uses data from the 431 shops that responded to both survey rounds.[4] Each survey was designed to monitor COVID-19 disruptions on the urban food retail sector, including both stated disruptions of operations and observed disruptions through food product prices.

To capture the equilibrium effects from both supply and demand shocks from COVID-19, we collected price data for both purchases (i.e., the price they paid to procure the product) and sales

[3] Author's estimates based on the seven-day dietary recall module in the 2017 Myanmar Living Conditions Survey (MLCS).

[4] There were nine observations of attrition between the two rounds of data collection.

(i.e., the prices charged to consumers). In the late August survey round, we asked shops to recall prices at three points in time to understand price movements during the pandemic. First, we recorded recall prices from early March 2020–before the stringent policy responses were applied–to serve as a pre-COVID-19 baseline. Then we asked shops to report both the highest and lowest prices experienced between April and August to understand price volatility during the crisis. In the September survey, we captured the food prices at the time of interview, again for both purchases and sales.

At each time we captured prices for a fixed list of specific food products. By asking about specific food products, we remove multiple sources of price variation–specifically, brand and quality–across time and across shops, allowing for more precise estimation of the effects of COVID-19 lockdowns on food prices. The list of specific food products was identified in the first survey round with open questions about which products retailers carry within three food categories: (i) perishable commodities that have unrefrigerated shelf lives of less than one month; (ii) shelf-stable staples with shelf lives longer than one month; and (iii) highly processed foods that are packaged and branded and have longer shelf lives. The most common items in each category were then selected as the fixed items for which we captured price data in later rounds. Less than 4 percent of shops sold fresh fruits and vegetables or meat products, so these categories are excluded from our price data. Consumers typically purchase these perishable items directly from wet markets or modern grocery stores.

On average, the shops in our study generated about 2,771,000 MMK (1,850 USD) per week in revenues prior to the pandemic (Table 1). Yangon shops had 20 percent higher revenues than shops in Mandalay, on average. However, the composition of revenues across food, non-food, and alcohol and tobacco products is similar in each city. Food products are the leading source of income, contributing to 60 percent of revenues, followed by non-food products with 25 percent, and alcohol and tobacco account for the remaining 15 percent of shop revenues.

Table 1. Sample descriptive statistics

	Total	Yangon	Mandalay
Number of townships in sample	37	30	7
Number of shops in sample	431	331	100
Weekly revenue before the pandemic (‘000 MMK)			
Mean	2,771	2,915	2,338
Median	800	800	750
Shop area (square feet)			
Mean	841	790	1,050
Median	600	600	725
Number of food retail competitors less than 100 meters from shop			
Mean	1.2	1.3	0.9
Median	1	1	1
Township percentage of vulnerable population			
Mean (%)	28	27	35
Median (%)	27	25	34
Mean percentage of revenue from different product categories before the pandemic			
Food (%)	60	61	59
Non-food (%)	25	24	27
Alcohol and tobacco (%)	15	15	14

Source: Urban food retailer survey, MIMU Township Vulnerability Dashboard.
Note: Competitors defined as grocers and small, permanent shops.

Shops in Yangon have smaller square footage on average and have more food retail competitors within 100 meters, which reflects the greater density of people and buildings in Yangon. However, townships in Mandalay have higher average shares of vulnerable populations according to MIMU

(2018), which uses a multidimensional vulnerability index using data on health, conflict, education, livelihoods, and other factors.

4. EMPRICAL FRAMEWORK

To estimate the effects of lockdowns on prices during the COVID-19 crisis, we use a fixed effects difference-in-differences (DiD) model with the following specification:

$$Y_{ijkt} = \alpha_i + \beta_1 Post_t + \beta_2 \left(Post_t \; x \; Lockdown_j\right) + \mu_k + \varepsilon_{ijkt} \qquad (1)$$

Y_{ijkt} is the dependent variable for shop *i*, township *j,* food item *k*, and time *t.* We estimate three sets of regressions with the following dependent variables: (i) consumer-facing prices, defined as the natural logarithm of selling prices; (ii) supply prices, defined as the natural logarithm of buying prices paid to procure the product; and (iii) percentage retail margin, defined as the selling price minus buying price (i.e., retailer margin) divided by the buying price. These three outcome variables will allow us to test for short-run equilibrium price effects to demand, supply, and retailer margin changes during lockdowns.

On the right-hand side, α_i is the shop-level fixed effect term. For each shop, we have multiple products *k* and times *t*. The fixed effect captures all shop characteristics that do not change over time or across products. Important attributes captured by this variable include the location of the shop in relation to both demand (i.e., in a residential or business area) and food supply (i.e., proximity to competition from supermarkets, wet markets, or other small shops) as well as shop ownership, management, and experience.

$Post_t$ is the time indicator variable equal to one for prices in September 2020 (during COVID-19) and equal to zero for prices in March 2020 before widespread COVID-19 policies were enacted. β_1 captures the average change in the dependent variable for townships not under lockdown or, in other words, the changes during the pandemic not attributable to the lockdowns in the second wave.

$Lockdown_j$ is a township-level indicator variable equal to one if the shop was in a township affected by lockdown in the September survey. Because lockdown implementation varied across townships, as described in Section 2, we construct this variable from respondent data, not from the government announced lockdown lists, which would be a weak indicator of lockdown impacts on the ground. If any shop reported a township lockdown, then we set $Lockdown_j$ to one for all the shops in that township. Conversely, if no shops in a township reported a lockdown, we set $Lockdown_j$ to zero. Because the lockdown variable is defined at the township level–a fixed attribute of the shops–the shop fixed effects absorb the base (i.e., pre-COVID-19) differences in lockdown townships, and $Lockdown_j$ only enters the righthand side through an interaction with $Post_t$. β_2 is the DiD estimator and our main effect of interest. It captures the average difference in changes during COVID-19 for townships under lockdown relative to those not under lockdown.

We also include a series of indicator variables for each food product, μ_k,that control for differences in average price and margin levels across products. Lastly, ε_{ijkt} is the error term clustered at the township level–the level at which our treatment variable is defined (Abadie et al. 2017) . We have 37 townships, a number which is generally on the border of "small" for asymptotic-based clustering procedures. To overcome potential errors in over-rejection rates caused by a small number of clusters, we also include wild cluster bootstrapped p-values for each estimate (Cameron et al. 2008).

4.1. Extensions

Our primary specification is to estimate equation (1) for all food products pooled together. This will show the overall changes in prices during the pandemic and under lockdowns. Yet, there may be important differences in estimated effects across food product categories. For instance, there may be variation in supply chain effects for different categories of products. To explore these potential differences, we also estimate equation (1) separately for the perishable, non-perishable staples, and highly processed food items.

Similarly, there may be important differences in the price and margin effects of lockdowns based on retailer characteristics. We thus extend our model to test for heterogeneous effects by interacting an indicator variable for the covariate of interest with both the $Post_t$ and $Post_t\ x\ Lockdown_j$ terms. We employ this method for four covariates. The first is a city indicator variable to differentiate effects between Yangon and Mandalay. The main food manufacturing and production zones in Myanmar are around Yangon, whereas Mandalay is geographically closer to agricultural production regions for onions and chickpeas. Thus, there may be differences in prices stemming from differences in transportation restrictions between the regions.

The second covariate is an indicator variable for a shop's size in square footage, defined as equal to one if greater than the sample median.[5] Larger shops may be more formal and have more direct and stronger ties to their supplier networks, while smaller shops may have a more robust base of consumers that may shield them from larger shifts in prices or margins.

The third covariate is a proxy for competition and the density of demand around each shop, which is defined as an indicator variable equal to one if the shop has more than one competitor (grocery store, chain retailer, or small shop) within 100 meters (one is the median value). Shops with more local competition may benefit from more robust relationships with suppliers but may also have more pressure on consumer-facing prices, which can prevent price increases.

The fourth and final covariate is a township-level variable for high and low vulnerability of the population. Again, we define an indicator variable based on the sample median. In this case, a value of one is assigned if the township has a share of vulnerable households above the sample median in each city. Household vulnerability is defined using a multidimensional index (MIMU 2018). From a food security standpoint, it is useful to know whether there are greater or lesser effects of lockdown policies in areas with more vulnerable populations.

4.2. Robustness check

The six-month span between March and September 2020 may have seen multiple price movements for some products whether due to seasonality for perishable products or to other less predictable shocks. Identifying the effects of lockdowns on prices and margins requires the assumption that those price movements were unrelated to our lockdown variable, i.e., that shops in lockdown townships did not systematically experience differences in price movements independent from the lockdown effects. Ideally, we would mitigate potential biases from temporal differences in price shifts by estimating the price and margin changes from immediately prior to the lockdown with those after the lockdowns had been implemented. We lack price data from immediately prior to lockdowns. However, in the August survey we asked each shop to report the highest and lowest buying and selling prices that occurred over the period from March to August. While these prices occurred at different times over that period, we can evaluate potential temporal biases by estimating two additional regression specifications of equation (1) using different baseline prices as comparisons to September: (i) using the highest reported price from March to August as the baseline; and (ii) using the lowest price as the baseline. We can then gauge whether the effects of lockdowns may be influenced by intermediate price fluctuations between March and August.

[5] We use the median as a simple threshold to test for differences because it balances the number of shops on each side of the threshold and increases statistical power in the estimated effects.

5. RESULTS

5.1. Descriptive analysis of COVID-19 impacts and food price distributions

The first six months of the COVID-19 crisis had clear effects on small food retailers in Myanmar. In September 2020, 54 percent of the sampled shops reported closing for at least one day due to the pandemic and 48 percent reduced their business hours. Yangon shops were more likely to report both disruptions, as were shops in lockdown townships (each difference is significant at the 10 percent level). While small and family-owned shops typically rely on family members for their labor, nonetheless 11 percent had employees unable to come to work due to the pandemic, with shops in lockdown townships being twice as likely to report labor disruptions than those outside of lockdown. However, the difference is not statistically significant. Ninety percent of shops adopted at least one safety measure to prevent the spread of COVID-19. Measures included wearing masks, social distancing within shops, and limiting the number of customers into the shop at a time. To cope with business shocks, 24 percent of the sample used personal savings to sustain business operations. Availability of savings is a contributing factor to resilience for small enterprises in Myanmar during the COVID-19 crisis given their lack of access to formal credit sources.

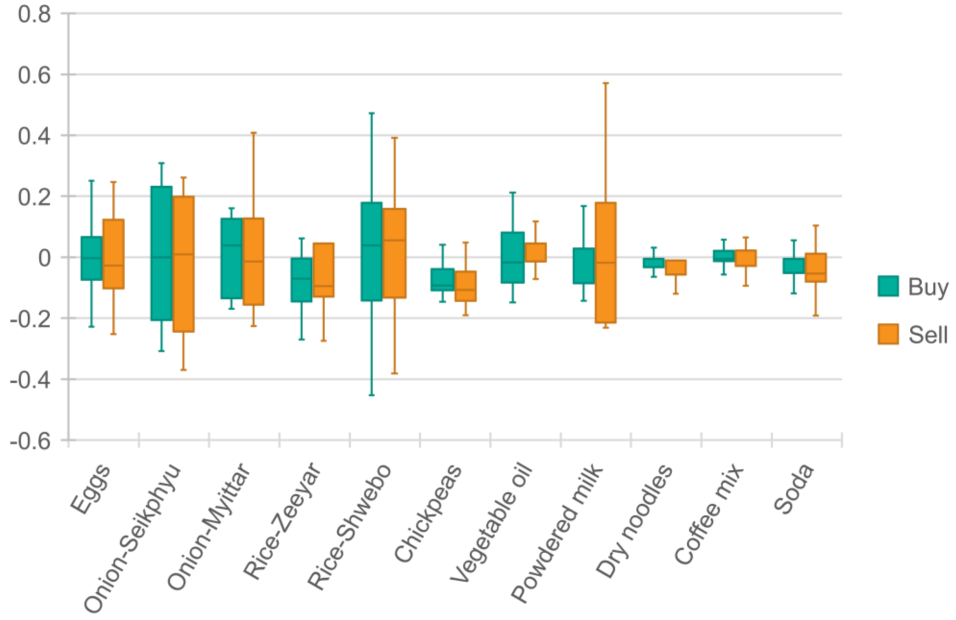
Table 2. Reported COVID-19 impacts in September 2020, share of shops reporting disruptions

		City				Lockdown		
	Total (%)	Yangon (%)	Mandalay (%)	Diff		No (%)	Yes (%)	Diff
Temporarily closed at least 1 day	54	57	44	**		43	56	**
Reduced business hours	48	50	40	*		40	50	*
Employees unable to come to work	11	12	8			6	12	
Adopt safety practices	90	88	94	*		91	89	
Use personal savings to finance business	24	22	28			22	24	

Source: Urban food retailer survey.
Note: Diff reports significant differences: *p<0.1, **p<0.05, ***p<0.01.

Controlling for both the product and the type of retail outlet, our detailed food price data for a fixed list of specific items provides an opportunity to explore food price distributions in urban areas. To compare the relative variance in buying and selling prices across products, we put the prices on similar scales and remove units of measure by applying the following transformation to each price observation: $\left(P_{ik}^{l}/\overline{P_{k}^{l}}\right) - 1$, where P_{ik}^{l} is the price for shop i, product k, and superscript l denotes the price type, either buying or selling. $\overline{P_{k}^{l}}$ is the average price of type l for product k. We subtract one from each observation to center the distribution means at zero. Note that this transformation will scale each price distribution but will not standardize the variances, which will be in percentage terms of the mean. Figure 3 shows boxplots of buying and selling price distributions from March 2020 for each product. The boxes represent the interquartile range (25^{th} percentile to the 75^{th} percentile) and contain 50 percent of the price observations, with lines extending up to the maximum and down to the minimum values, respectively.

Figure 3. Buying and selling price distributions by food products in March 2020



Note: Distributions are standardized to show relative variations. Outliers not displayed but included in calculations.

There is considerable price variation across shops both in procurement and consumer-facing prices, particularly for perishable and shelf-stable commodities. These products are largely sourced through wholesale markets and may exhibit some differences in quality, branding, or packaging across shops. The buying and selling price distributions for products in these categories closely mirror each other, suggesting that price variations in procurement may be passed through to consumers with limited distortions or variations in margins. Interestingly, there are big differences across the two rice varieties in our data. Shwebo rice shows much higher variance than Zeeyar rice. Shwebo is in the Pawsan family, which is highly preferred among Myanmar consumers and has higher prices and wider variance than other less preferred varieties (Goeb et al. 2021). Zeeyar rice, however, does have some high price observations, which shift the boxplots below zero on the y-axis. A similar effect is seen for chickpeas.

In contrast to perishables and shelf-stable staples, the highly processed products have generally much tighter distributions, particularly for buying prices. These products have greater quality homogeneity–they are branded and packaged the same–and more formal supply chains with most shops buying from food companies directly. Interestingly, sales prices show much more variation than buying prices, suggesting that consumer prices vary across shops despite relatively standardized buying prices. This is especially true for powdered milk and is also noticeable for soda.

Having observed the price distributions for each product prior to the pandemic, we now turn our attention to price changes over the first six months of the COVID-19 crisis. In general, changes for both buying and selling prices were modest (Table 3). Onions are the exception with observed price increases of more than 20 percent in non-lockdown townships and more than 40 percent in lockdown townships (insignificant difference). This is a special case related to increased export demand (Sumon 2020) and not to domestic COVID-19 policies. Eggs, the other perishable commodity, also experienced above average price changes. As a category, highly processed foods show the smallest price changes, though soda and vegetable oil had large increases for the townships under lockdown. For nearly every product, both buying and selling price changes were higher under lockdown–powdered milk is the lone exception. There are statistically significant differences (at the 10 percent level) in buying prices of chickpeas and vegetable oil and in buying and selling prices of soda (at the 1 percent level).

Table 3. Changes in prices from March to September 2020, mean retailer margins, and changes in supplier networks by product

	Price changes (%)						Percentage margins[1]						Share of shops that changed suppliers		
	Buy			Sell			March			September					
Lockdown?	No	Yes	Diff	No	Yes	Diff	No	Yes	Diff	No	Yes	Diff	No	Yes	Diff
Perishables															
Eggs	6	9		2	6		23	24		18	21		7	8	
Onions	20	48		24	45		24	22		28	21	**	18	29	
Shelf-stable staples															
Rice	1	6		1	5		11	12		11	12		9	4	
Chickpeas	-6	3	*	-4	8		13	11		22	16		25	14	
Highly processed foods															
Vegetable oil	5	8	*	3	4		12	14		10	10		4	3	
Powdered milk	0	1		1	-1		20	18		20	16		9	7	
Dry noodles	0	1		3	5		18	17		21	22		9	13	
Coffee mix	0	0		0	0		10	9		10	9		9	7	
Soda	-2	13	***	-1	12	***	16	16		17	15		0	9	

Note: these are paired changes at shop level, so means are percentage changes at shop-product level.
[1]Percentage margins defined as = 100 * (sell price - buy price) / buy price.
'Diff' reports statistically significant differences: *p<0.1, **p<0.05, ***p<0.01

For most products, the buying price changes are similar in magnitude to the selling price changes. However, there are large percentage point gaps in the two for chickpeas and dry noodles, which both show larger changes in selling prices than buying prices. Chickpeas and dry noodles also show the largest increases in retailer margins between March and September. Other products, as expected from the similar buying and selling price changes, show modest changes in average percentage margins, suggesting that there was unlikely to be any price gouging or opportunistic behaviors at the expense of consumers. Overall, perishable products exhibited the highest margins, while products with longer shelf lives–shelf-stable staples and highly processed foods–show smaller margins. Further, the patterns in margins and the percentage point changes between March and September are mostly similar in lockdown and non-lockdown townships. There are no statistically significant differences in March, while the only significant difference in September is for onions.

The last point to draw from Table 3 is that there were only modest disruptions to supply chains during the pandemic. While we do not have a counterfactual of supply chain changes under usual circumstances, in September most shops selling each product were able to source them from their usual suppliers. Onions had the largest share of retailers changing suppliers overall, likely reflecting supply decreases due to rising export demands. Interestingly, the next two products with the largest shifts in suppliers were, again, chickpea and dry noodles, perhaps suggesting some disruptions in their supply chains. Two of the more important food items for consumers, rice, the staple food, and vegetable oil had the smallest supplier changes overall. There were no statistically significant differences across lockdown and non-lockdown townships.

The higher price changes in lockdown townships do not appear to be strongly linked to supplier changes. Shops in lockdown townships had higher shares of shops change suppliers for five products, while non-lockdown townships showed larger changes for four products. This suggests that increased costs along the supply chain, rather than major disruptions in supplier networks, may be driving observed price changes. Overall, 90 percent of products were sourced from their usual suppliers in September.

5.2. Regression results

We now turn to regression analysis to explore the effects of township lockdowns on prices in more detail. Table 4 shows the estimation results of equation 1 for all products and separately for the three product categories. There are several important results to highlight from these pooled regressions.

In the townships that did not experience a lockdown in September, overall changes during the pandemic to both buying and selling prices and to margins were small and not statistically different from zero. Thus, on average, the COVID-19 disruptions and policies implemented between March and September did not result in significantly higher or lower prices. However, in townships where lockdowns were implemented, there were modest but significant price increases. Consumer facing prices increased by 2.9 percent above the non-lockdown townships, significant at the 1 percent level. Buying prices for retailers similarly increased by 3.4 percent more in lockdown townships, also significant at 1 percent level. Retailer margins did not meaningfully change, suggesting that higher buying prices were mainly passed through to consumers. The total price increases during the pandemic for lockdown townships were 3.9 percent for selling prices and 3.8 percent for buying prices, while percentage margins increased by only 0.2 percentage points.

Table 4. Lockdown effects on food product buying and selling prices, all products and by category

	All products			Perishable			Shelf-stable staples			Highly processed foods		
Dependent variables:	**ln(buy price)**	**ln(sell price)**	**% margin**	**ln(buy price)**	**ln(sell price)**	**% margin**	**ln(buy price)**	**ln(sell price)**	**% margin**	**ln(buy price)**	**ln(sell price)**	**% margin**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**
Post	0.004	0.010	0.008	0.107***	0.097***	-0.010	-0.042	-0.019	0.041	-0.005	0.001	0.006
	(0.008)	(0.008)	(0.007)	(0.013)	(0.018)	(0.014)	(0.039)	(0.025)	(0.049)	(0.007)	(0.009)	(0.006)
	[0.740]	[0.335]	[0.399]	[0.003]	[0.022]	[0.442]	[0.481]	[0.484]	[0.946]	[0.465]	[0.914]	[0.380]
*Post * Lockdown*	0.034***	0.029***	-0.006	0.055*	0.046	-0.014	0.069	0.062*	-0.018	0.027***	0.024**	-0.003
	(0.009)	(0.010)	(0.008)	(0.027)	(0.028)	(0.019)	(0.043)	(0.031)	(0.052)	(0.008)	(0.010)	(0.007)
	[<0.001]	[0.002]	[0.524]	[0.089]	[0.166]	[0.444]	[0.183]	[0.045]	[0.888]	[0.004]	[0.013]	[0.684]
Shop-level fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Product dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,990	2,990	2,990	290	290	290	268	268	268	2,432	2,432	2,432
R-squared	0.988	0.986	0.197	0.890	0.886	0.033	0.975	0.971	0.059	0.985	0.983	0.215

Note: Significance levels: *p<0.1, **p<0.05, ***p<0.01. Cluster robust SEs at the township level in parentheses. Wild cluster bootstrapped p-values in brackets.
Post is the time indicator variable equal to one for prices in September 2020 (during COVID 19) and equal to zero for prices in March 2020 (before widespread COVID 19 policies were enacted).
Lockdown is a township-level indicator variable equal to one if the shop was in a township affected by lockdown in the September survey.

Table 4 also reveals interesting patterns in the effects across product categories. There were large significant price increases for perishable food items for shops not under lockdown, likely due to the large increase in onion prices documented in Table 3. However, estimates for shelf-stable staples and highly processed foods were insignificant. This pattern suggests that there were no major demand shifts and that the agri-food system largely adjusted to the policies and movement restrictions during the first wave of COVID-19 in Myanmar so that food was supplied to urban consumers at similar prices to those prior to the pandemic. However, in each food product category, there is evidence that lockdowns led to small but statistically significant price increases.

The largest price increases were for shelf-stable staples, for which buying prices increased by 6.9 percent and consumer-facing prices increased by 6.2 percent (significant at the 5 percent level). Similar, but slightly smaller increases occurred for perishable commodities sold by shops under lockdown. Buying prices increased by 5.5 percent (significant at the 10 percent level) and consumer prices increased by 4.6 percent. Highly processed foods had the smallest lockdown effect sizes, but the strongest statistical significance due to smaller variances. Highly processed food buying prices increased by 2.7 percent (significant at the 1 percent level) and selling prices increased by 2.4 percent (significant at the 5 percent level) during lockdowns. Lastly, overall and for each food category, percentage margins did not significantly change during COVID-19 in either the non-lockdown or lockdown townships.

5.3. Heterogeneous effects

Table 5 presents tests of heterogeneous effects across four covariates which could be related to the strength and resilience of the connections of shops to suppliers on the supply side or to their base of consumers on the demand side. The first covariate test shows (Table 5, columns (1) and (2)) that the lockdown effects were not significantly different in Mandalay compared to Yangon, suggesting that lockdowns had a similar impact on prices in both cities. Yet, in townships without lockdowns, price increases were 2.8 and 2.4 percent higher in Mandalay than Yangon for buying and selling prices, respectively. Most processed food products are produced in or around Yangon. Thus, the higher price changes in Mandalay may be explained by increased transportation costs due to travel restrictions intended to curb COVID-19. Differences in consumer demand patterns could also be a driver of the differences across cities.

Larger shops–those with square footage greater than the median–had smaller estimated impacts of lockdowns on prices, with effect sizes about 4 percent lower than smaller shops (Table 5, columns (3) and (4)). These results could be driven by the supply side, such as through stronger relationships to their supplier networks, or the demand side, such as through a larger more consistent pool of customers. The negative effect for large shops is unlikely to be influenced by the products that shops carry. Large and small shops show similar patterns in the food products they sell, with the exception of shelf-stable staples which have the largest price increases in lockdown townships and account for a higher share of foods sold for large shops (11 percent) than for small shops (7 percent).

The third covariate, a measure of local competition, shows that shops with more food retail outlets nearby had lower price changes during the pandemic in non-lockdown townships, but higher price changes in townships under lockdown (Table 5, columns (5) and (6)). A possible explanation is that suppliers must deliver larger quantities of supplies in an area with more shops. This requires more frequent trips or the use of larger trucks, which may have been difficult in lockdown townships.

Table 5. Heterogenous effects of lockdowns on food product buying and selling prices, all products

Dependent variables:	ln(buy price) (1)	ln(sell price) (2)	ln(buy price) (3)	ln(sell price) (4)	ln(buy price) (5)	ln(sell price) (6)	ln(buy price) (7)	ln(sell price) (8)
post	-0.006	0.002	-0.009	-0.001	0.011	0.018**	0.012	0.011
	(0.008)	(0.010)	(0.008)	(0.009)	(0.009)	(0.008)	(0.010)	(0.012)
	[0.474]	[0.855]	[0.296]	[0.944]	[0.374]	[0.140]	[0.555]	[0.677]
post * lockdown	0.040***	0.034***	0.055***	0.049***	0.023**	0.016	0.038***	0.035**
	(0.009)	(0.011)	(0.011)	(0.012)	(0.011)	(0.010)	(0.012)	(0.014)
	[0.000]	[0.006]	[0.000]	[0.000]	[0.031]	[0.129]	[0.007]	[0.014]
post * Mandalay	0.028***	0.024**						
	(0.009)	(0.011)						
	[0.079]	[0.223]						
post * lockdown * Mandalay	-0.014	-0.007						
	(0.017)	(0.018)						
	[0.462]	[0.726]						
post * LargeShop			0.026**	0.022				
			(0.011)	(0.015)				
			[0.082]	[0.275]				
post * lockdown * LargeShop			-0.044***	-0.040**				
			(0.014)	(0.017)				
			[0.022]	[0.058]				
post * HighCompetition					-0.024**	-0.027*		
					(0.010)	(0.014)		
					[0.057]	[0.137]		
post * lockdown * HighCompetition					0.032**	0.040**		
					(0.015)	(0.017)		
					[0.052]	[0.034]		
post * HighVulnerable							-0.024**	-0.013
							(0.011)	(0.017)
							[0.168]	[0.530]
post * lockdown * HighVulnerable							0.002	0.000
							(0.014)	(0.019)
							[0.885]	[0.985]
Shop-level fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Product dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,990	2,990	2,990	2,990	2,990	2,990	2,887	2,887
R-squared	0.988	0.986	0.988	0.986	0.988	0.986	0.988	0.986

Note: Significance levels: *p<0.1, **p<0.05, ***p<0.01. Cluster robust SEs at the township level in parentheses. Wild cluster bootstrapped p-values in brackets.

The fourth test for heterogeneity shows that townships with higher shares of more vulnerable populations have statistically similar price changes during lockdowns as those with less vulnerable populations (Table 5, columns (7) and (8)). Further, the price changes in non-lockdown townships are lower for more vulnerable townships, and the effect estimate for buying prices is statistically significant. Although it is encouraging that areas with greater shares of vulnerable people did not have higher price changes, we note that any food price increases likely had a greater relative impact on more vulnerable households.

Lastly, our estimations on the percentage margin outcome variable, while not presented in Table 5, show no significant heterogeneous effects across any of the covariates tested. Shifts in prices are transmitted to consumers at similar rates under lockdown and not under lockdown, confirming and extending our base estimation result.

5.4. Robustness checks

In the six-month gap between the baseline prices from March 2020 and the endline prices from September 2020, there may have been systematic price changes across lockdown and non-lockdown townships that could bias our estimates. Table 6 presents robustness check estimations of the main results with all food products pooled together, but with two separate shop and product-level baseline prices: the highest and lowest prices reported between March and August. The results show that the estimated effects of lockdown are not sensitive to temporal variations in prices. The different base prices change the effect estimates of lockdown by no more than 0.005 on buying and selling prices and on percentage margins. Further, the statistical significance is similar, with all price estimations significant at the 1 percent level, while the percentage margin estimations remain insignificant.

Table 6. Lockdown effects on buying and selling prices using high and low prices as baseline

	ln(buy price)		ln(sell price)		% margins	
Baseline price:	High price	Low price	High price	Low price	High price	Low price
	(1)	(2)	(3)	(4)	(5)	(6)
Post	-0.019**	0.013	-0.012	0.018*	0.011	0.005
	(0.008)	(0.009)	(0.010)	(0.009)	(0.008)	(0.007)
	[0.017]	[0.269]	[0.212]	[0.165]	[0.226]	[0.499]
*Post * Lockdown*	0.033***	0.034***	0.034***	0.031***	-0.002	-0.004
	(0.009)	(0.010)	(0.011)	(0.010)	(0.008)	(0.007)
	[0.000]	[0.005]	[0.001]	[0.003]	[0.850]	[0.587]
Shop-level fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Product dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,989	2,990	2,990	2,990	2,989	2,990
R-squared	0.988	0.987	0.986	0.986	0.201	0.191

Note: Significance levels: *p<0.1, **p<0.05, ***p<0.01. Cluster robust SEs at the township level in parentheses. Wild cluster bootstrapped p-values in brackets.
High and low prices are the highest and lowest reported prices, respectively, between March and August 2020.

6. DISCUSSION AND CONCLUSION

We examined business disruptions of urban food retailers under the shock of a lockdown and estimated how prices and margins in the traditional urban food retail sector were impacted by lockdowns during Myanmar's second wave of COVID-19. Results from a panel phone survey conducted with a novel sample of small, family-owned retailers indicate non-trivial disruptions to business operations from COVID-19 policies.

We used a shop-level fixed effects difference-in-difference model to estimate the impacts of a township-level lockdown on supplier prices, consumer-facing prices, and retailer percentage margins. Our results show that supply chains for the food products studied were mostly resilient six months into the pandemic. Overall, buying and selling prices were not statistically significantly different from their pre-pandemic levels for shops unaffected by lockdowns. However, lockdowns implemented in a sub-set of townships significantly increased food prices. The effects were modest overall, with prices rising by about 3 percent. However, the estimates were larger at between 5 and 7 percent for less processed food items that comprise a large share of urban diets, including rice, eggs, and onions. Retailer margins were consistently unaffected by COVID-19 policies and by lockdowns specifically. Price changes on the supply side were largely transmitted through to consumers and retailers and neither absorbed nor magnified price changes through lower or higher margins. Thus, we found no evidence of price gouging in our sample, which could be related to the competitiveness of the traditional food retail sector and to the low market power of each shop. Finally, price changes were lower in non-lockdown townships with higher shares of vulnerable people, and the estimated lockdown effects were not significantly different between more and less vulnerable townships. This is an encouraging result because poor households often pay higher prices for foods, but the COVID-19 pandemic does not appear to have amplified those differences in the traditional urban food retail sector in Myanmar.

The analysis presented in this paper has limitations. First, we focused only on the short-term impacts of a lockdown. While lockdowns are often short in nature, during the COVID-19 crisis some extended for many weeks. In the medium and long term, there may be more sustained disruptions, although supply chains would also be given more time to respond. Further research should explore these longer-term effects. Second, our analysis centered on locally produced and manufactured products. While local products comprise the majority of foods consumed in Myanmar, imported foods have longer supply chains that may suffer more severe effects from COVID-19 restrictions, though the township-level lockdowns analyzed in this paper may or may not have differential impacts for imports. In countries where imported foods are more important, researchers should also consider potential trade-related effects of lockdowns on their prices. Third, we studied only the traditional retail sector in the two main cities of Myanmar, which is an important food retail channel, but not the only one. Further research should explore lockdown impacts on modern supermarkets and wet markets.

Our findings reinforce the policy advice voiced frequently in the food systems literature: it is essential to keep the food supply chain–including wholesale markets and retail shops–functioning as completely and as safely as possible during times of crisis and lockdowns. Our results show that lockdowns have a modest but significant impact on food prices. These impacts should be considered when implementing future movement restrictions. More specifically, less processed foods that are sourced from wholesale markets and comprise the bulk of urban diets may be more sensitive to lockdowns.

Finally, the variation in prices across shops for specific food items suggests that the costs of urban diets are highly context specific. A consumer's location may determine his or her access to different food markets, which in turn may impact the cost of buying a fixed basket of foods. Future research on estimates of urban diet costs should make efforts to account for these variations.

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INTERNATIONAL FOOD POLICY RESEARCH INSTITUTE
1201 Eye St, NW | Washington, DC 20005 USA
T. +1-202-862-5600 | F. +1-202-862-5606
ifpri@cgiar.org
www.ifpri.org | www.ifpri.info

IFPRI-MYANMAR
No. 99-E6 U Aung Kein Lane
Than Lwin Road, Bahan Township
Yangon, Myanmar
IFPRI-Myanmar@cgiar.org
www.myanmar.ifpri.info

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