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# The tale of two countries: Modelling the effects of COVID-19 on shopping behaviour in Bangladesh and India

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**Abstract:**

This paper explores the impact of COVID-19 on shopping behaviour in two developing economies of South Asia: Bangladesh and India. While the previous studies investigating the impact of COVID-19 on shopping behaviour have relied on Revealed Preference (RP) data, this paper combines RP and Stated Preference (SP) data to develop joint RP-SP discrete choice models. This makes it possible to quantify the relative impact of the situational contexts (e.g. number of cases and deaths in the country, number of family members affected by the virus, etc.) on the choice of shopping modes of households and to capture the associated heterogeneity arising from the characteristics and the pre-COVID behaviour of the households. Further, comparison of the data and the estimated model parameters of the two countries with substantial socio-cultural similarities provide insights about how differences in the state of e-commerce can lead to different levels of *inertia* in terms of continuing the pre-COVID behaviour. The results will be useful to planners and policymakers for predicting the shopping modes in different future scenarios and formulating effective restriction measures.

**Keywords:** COVID-19, pandemic, shopping, Bangladesh, India, revealed preference, stated preference, choice model

## 1. Introduction

The coronavirus (COVID-19) pandemic has resulted in disruptive changes in our day-to-day activity patterns and lifestyle (Nicola et al., 2020). These are not only prompted by the restrictions imposed by the Government and the flexibility offered by the employers, but also by the personal awareness to maintain social distance for self-protection and protection of the others (Bucsky, 2020) and perceived risks associated with visiting public and pseudo-public spaces (e.g. plazas and shopping centres) and interacting with others (Honey-Rosés et al., 2020). The changes in travel behaviour include reductions in trip numbers, trip lengths and modal shifts (Bhaduri et al., 2020). For instance, public transport ridership has been affected significantly (Park, 2020, Almlöf et al., 2020, Musselwhite et al., 2020, Bucsky, 2020, De Vos, 2020); people have switched to active modes and micro-mobility has been on the rise (Aloi et al., 2020, Barbarossa, 2020, Bucsky, 2020, Campisi et al., 2020, Shamshiripour et al., 2020, de Haas et al., 2020); and shared on-demand modes like Uber Pool have become less popular than before (Bhaduri et al., 2020). Though these changes have led to some positive impacts like reduced congestion, pollution, and noise (Saadat et al., 2020), it has also taken a toll on the revenue of the transport authorities and transportation network operators (Gkiotsalitis and Cats, 2020, Hensher, 2020). All these unprecedented changes and challenges suggest the necessity of gaining a deeper understanding of emerging behavioural pattern (e.g. remote working, remote shopping etc.) for sustainable transport policy and planning in the 'new-normal'.

The recent studies conducted so far to understand the extent of the emerging behavioural pattern have revealed a marked change in shopping behaviour (Shamshiripour et al., 2020). For instance, a significant number of people have been observed to shift to online shopping (Grashuis et al., 2020, Matson et al., 2021, Chen et al., 2021), while results have also shown the trend to shop locally either by using active mode or by using private modes (Abdullah et al., 2020). Accumulated evidence indicated that in many countries, the primary purpose to travel during the pandemic has been essential shopping (Abdullah et al., 2020) but mobility requirements for the groceries vary substantially between different socio-economic groups (Molloy et al., 2020, Abdullah et al., 2020, Shakibaei et al., 2020). Such changes in shopping behaviour also have impact retail and wholesale shop as well as at the logistic supply chain (Ivanov, 2020, Li et al., 2020).

While traditionally (pre-COVID), the most frequently used mode for shopping trips was trips to stores using the personal vehicle (Meena et al., 2019), a notable shift has been observed from in-person shopping to online shopping, especially in the developed countries. For example, in the United States, the usual market share of online retailers (about 3–4%) has increased to 10–15% during the COVID-19 pandemic (Repko, 2020). In addition, a global consumer behaviour survey conducted by Capgemini Research Institute in April 2020, which includes India, reveals that there is approximately a 35% dip in the levels of interaction that consumers have had with physical stores since the COVID-19 outbreak. This is coupled with a 7% increase in the levels of interaction that consumers have had with online platforms for daily shopping needs during the same timeframe. The research also estimates that during the following 6 to 9-month period, consumer interaction with physical stores is likely to remain below the pre-COVID levels, whereas a 10% increase is expected in online consumer interactions as compared to the pre-COVID levels (Capgemini, 2020, Grashuis et al., 2020). conducted a Stated Preference (SP) study among online grocery shoppers in the US and found that the trend in COVID infection rates (increasing, decreasing or constant) have a significant impact on the sensitivity to factors like cost and flexibility with the willingness-to-pay for online services increasing when COVID-19 spreads at an increasing rate. The study however ignored the potential hypothetical bias and the behavioural incongruence that affects the results based only on SP data.

On the other hand, in the Global South, the current shopping culture, as well as the state of e-commerce and technology penetration, are significantly different from the developed countries (Pendyala et al., 2009). For instance, online services are not widely available in many parts of South Asia and/or not affordable options to many segments of the population. Also, these services are often subject to reliability and quality issues (Butt et al., 2016). Further, online shopping may not be the most preferred medium due to social and cultural factors (SivaKumar and Gunasekaran, 2017, Xi et al., 2020) though the situation is going through a rapid change due to the recent increase in penetration of internet services and growth in e-commerce (IBEF, 2019). For instance, in 2019, the online grocery retail market in metropolitan cities of India witnessed a growth rate of approximately 25-30% (Businesswire, 2019). Reports from various agencies suggest that during the successive COVID-19 lockdown periods as well as the unlock phases, online grocery market in India has shown an increase of 76-80% over last year, as aggregators such as Zomato, Swiggy, etc. have also started delivering groceries to individual customers (Lal, 2020). A study carried out by McKinsey shows that 15-30% of consumers in India expect to make higher portions of their purchases online post-COVID19 compared to before (McKinsey&Company, 2020). On the other hand, in the context of Bangladesh online grocery shopping was available primarily in the capital city pre-COVID (that too in very limited scale). Results of a study by Neger and Uddin (2020) demonstrate that in Bangladesh, factors such as product availability/quality, time-saving, payment means, and other administrative and psychological factors have a strong association with the internet shopping behaviour during the COVID-19 pandemic.

While, these studies indicate substantial shifts in shopping behaviour due to the pandemic, to the best of our knowledge, there has not been any research to date that mathematically models how the contextual factors like the number of COVID-19 affected people, the number of deaths, and different levels of government restrictions affect the shopping behaviour in the developing countries. There is also a need to investigate the extent of heterogeneity in behaviour among different socio-demographic groups in different future scenarios. This research aims to fill in this research gap by investigating the following research questions:

1. How do the changes in the shopping behaviour due to COVID-19 vary among different socio-demographic groups in Bangladesh and India?
2. What is the relative impact of general COVID-19 situation (e.g. number of affected people, death rates), personal circumstances (number of people experiencing COVID like symptoms) and Government restrictions on shopping behaviour in the two countries?
3. What is the extent of similarities and differences in shifts in shopping behaviour due to COVID-19 in two countries and if there are prospects of spatial transferability of the findings?

Stated preference (SP) data is collected in conjunction with Revealed Preference (RP) data in this regard which are used to develop joint RP-SP models to predict the demand for different mediums of shopping in different hypothetical future scenarios. It may be noted that the scope of shopping was limited to purchase of essential goods like food, medicine and other day-to-day essentials The rest of the paper is organised as follows: Section 2 presents the details of the survey and the sample characteristics. The model structure is presented in section 4, followed by the results in section 5. The last section summarizes the findings and discusses policy implications.

## 2. Data

### 2.1. Data source and survey design

The timeline of COVID-19 pandemic in India and Bangladesh is shown in Figure 1.

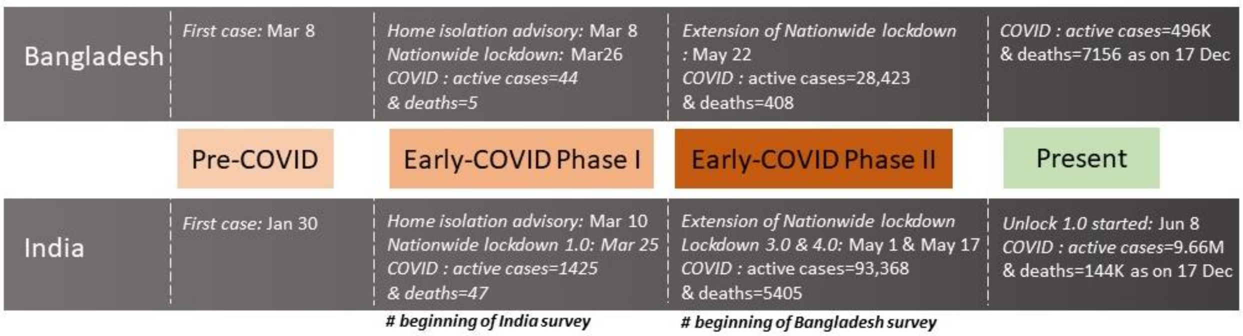



Figure 1: Timeline of COVID-19 related major events in Bangladesh and India

The data used in this study was collected through an online questionnaire survey circulated in Bangladesh (between 22 May- 29 May 2020) and India (between 24 March - 12 April 2020). In the survey, the respondents were asked about their weekly shopping patterns for daily necessities during pre-COVID-19 (regular days in January 2020) and during-COVID-19 period (March 2020 in India and April 2020 in Bangladesh). This led to two sets of RP observations per respondent. The same respondents also participated in an SP survey with two hypothetical COVID-19 scenarios with different Government restrictions and numbers of affected people and deaths (see **Appendix B** for details of the SP questionnaire). Respondents were recruited using various social media platforms (Facebook, LinkedIn, Twitter, WhatsApp and Instagram) using both unpaid (individual social circles, professional groups such as Planners Forum of Bangladesh, Transport Research Group of India, etc.) and paid (Facebook marketing) campaigns to enhance the reach of the survey as well as to minimize sampling bias as far as possible. Such dissemination technique was deemed as the best feasible option in the view of countrywide lockdown (imposed in India and Bangladesh on 25$^{th}$ and 26$^{th}$ March onwards respectively) which made the face-to-face survey option infeasible. In particular, the Facebook (paid) advertisement campaign allowed us to reach the intended target group both spatially and based on socio-demographic information and aided in obtaining a more diverse sample across both countries as opposed to a mere convenience sample. The collected data included shopping behaviour of 317 and 498 households from different cities in Bangladesh (39.43% respondents were from the capital city Dhaka and 60.57% respondents were from elsewhere) and India (40% respondents were from big cities[2] and 60% from small towns) respectively.

The survey questionnaire included 4 major sections — (a) pre-COVID-19 shopping behaviour (i.e. January 2020) (b) during-COVID-19 shopping behaviour (March in India and April in Bangladesh) and (c) stated shopping behaviour in two hypothetical COVID-19 scenarios (d) detailed socio-demographics. The questions about shopping behaviour in the "during-COVID-19" and SP scenarios included means of shopping (in-person or not) and if in-person, details of the modes used over a week and the maximum distance travelled. Information about behaviour over the week was collected instead of over a day as evidence from the literature suggests that for discretionary activity participation, it is quite likely that simple 1-day data sets (or even multi-day data sets) may not capture the range of choices that people are exercising with respect to their activity engagement (Spissu et al., 2009). The SP scenarios varied in terms of number of people affected in the country, the death rate in the administrative unit[3], number of people affected in the household and whether any strict government restriction (i.e. lockdown) is in place or not. A D-Optimal design was used in designing the scenarios[4] using the Ngene software (ChoiceMetrics, 2012).

It may be noted that though both countries have some travel modes in common, there are some differences in the choice sets among the two cases (Table 1).

[2] Cities with population > 1 million

[3] In case of Bangladesh, this referred to administrative divisions while in case of India, this referred to states (which was deemed to be more easily relatable to the respondents). There are 8 administrative divisions in Bangladesh and 29 states in India.

[4] Appendix B provides examples of corresponding SP scenarios presented in Bangladesh and India.

Table 1: List of shopping modes in Bangladesh and India during pre-COVID time

<table>
<tr><th>Modes</th><th>Bangladesh</th><th>India</th></tr>
<tr><td colspan="3">In-person</td></tr>
<tr><td>Active (walking and cycling)</td><td>x</td><td rowspan="2">x</td></tr>
<tr><td>Rickshaw (pedalled 3-wheeler)</td><td>x</td></tr>
<tr><td>Private car</td><td>x</td><td>x</td></tr>
<tr><td>Motorcycle</td><td>x</td><td>x</td></tr>
<tr><td>Access to office car for personal trips</td><td>x</td><td>-</td></tr>
<tr><td>Public transport (bus)</td><td>x</td><td rowspan="2">x</td></tr>
<tr><td>Public transport (metro rail and suburban rail)</td><td>-</td></tr>
<tr><td>Tempo/Human hauler (shared 3 or 4 wheelers with a capacity between 6-12)</td><td>x</td><td>-</td></tr>
<tr><td>Auto Rickshaw (CNG powered 3-wheeler taxis)</td><td>x</td><td>x</td></tr>
<tr><td>Private taxi</td><td>-</td><td>x</td></tr>
<tr><td>Ride-hailing service (car)</td><td>x</td><td>x</td></tr>
<tr><td>Ride-hailing service (motorcycle)</td><td>x</td><td>-</td></tr>
<tr><td colspan="3">Remote Options</td></tr>
<tr><td>Online</td><td>x</td><td>x</td></tr>
<tr><td>By phone</td><td>x</td><td>-</td></tr>
<tr><td>From Street vendor</td><td>x</td><td>-</td></tr>
<tr><td>With the help of local friends or neighbours</td><td>x</td><td>-</td></tr>
<tr><td>With the help of relatives living in the rural or suburban area</td><td>x</td><td>-</td></tr>
</table>

Further, though the questionnaires were very similar, the survey conducted in India covered non-commute trips (which may include some essential social visits[5] in addition to essential shopping), the one in Bangladesh focused only on essential shopping trips [6](as non-essential travel was prohibited during the period of data collection). On the other hand, in the sections on demographics, the survey conducted in India asked for some additional person-specific information (age, gender and employment category) in addition to the household socio-demographic questions (household size, household income, number of vulnerable members in the household). Moreover, in the case of the SP data, though the number of attributes, levels and the design was kept the same in both cases, the presented attribute values had to be varied to match the local context. For instance, since the total population in India is much higher, the total numbers of affected people and deaths presented in the SP scenarios were higher compared to Bangladesh.

[5] Essential social visits include trips to care for elderly or vulnerable relatives, friends or neighbor, such as dropping shopping or medication at their door

[6] Essential shopping trips include trips for daily necessities such as food, grocery, medicine etc.

### 2.2. Sample characteristics

Comparison of the household characteristics in the sample with the corresponding population values is presented in Table 2a. Given the differences in the share of household income in the sample and the census, the samples were weighted to match the census shares before the model estimation to increase the representativeness.

The vehicle ownership levels in the two samples are compared in Table 2b. As seen in the table, the car, motorcycle and bicycle ownership levels in the sample from India are higher in general compared to the sample from Bangladesh. However, the share of households owning more than one car is slightly higher in the sample from Bangladesh. The share of households owning more than one motorcycle is more than double in the sample from India compared to that of Bangladesh.

Table 2: Sample characteristics of socio-demographic variable

(a) Comparison between the sample and the census of the respective countries

| Variables | Categories | Bangladesh | | India | |
|---|---|---|---|---|---|
| | | Sample distribution (%) | Distribution* in urban population (%) | Sample distribution (%) | Distribution* in urban population (%) |
| Average household size | | 4.64 | 5 | NA | NA |
| Monthly household income (BDT for Bangladesh and INR for India***) | Low income HH (0-25 K) | 20.19 | 40 | 24.2 | 52.3 |
| | Middle income HH (>25-75 K) | 41.64 | 50 | 49.4 | 34.7 |
| | High-income HH (more than 75 K) | 38.17 | 10 | 26.4 | 13.0 |

* Census Data Bangladesh, 2011 (BBS, 2011, Rahman, 2016); ** (IHDS, 2011)
*** 1 BDT = 0.012 USD, 1 INR = 0.013 USD

(b) Comparison of vehicle ownership in the two samples

| Vehicle ownership | Categories | Bangladesh (%) | India (%) |
|---|---|---|---|
| Car ownership | No car | 76.97 | 65.2 |
| | 1 car | 18.61 | 31.8 |
| | 1+ car | 4.42 | 3.0 |
| Motorcycle ownership | No motorcycle | 79.18 | 49.8 |
| | 1 motorcycle | 17.67 | 43.0 |
| | 1+ motorcycle | 3.15 | 7.2 |
| Bicycle ownership | No bicycle | 79.50 | 61.6 |
| | 1 bicycle | 18.30 | 36.0 |
| | 1+ bicycle | 2.20 | 2.4 |

## 2.3. Comparison of shopping patterns

The similarities in socio-economic characteristics and social norms are expected to result in some similarities in the shopping patterns between the two countries. For instance, the role of online shopping is not as dominant in these countries as the high-income countries (Alyoubi, 2015, Karim and Qi, 2018). Furthermore, due to the presence of domestic support-staff members in the households (to help with the daily chores like shopping, cooking, cleaning, etc.), the frequency of essential shopping trips is also expected to be higher than the high-income countries. On the other hand, it is expected that there will be subtle differences in the shopping cultures as well due to the different rates of technology adaptation, transport landscape and Government interventions (e.g. in Bangladesh new open-air grocery-markets were set-up (Amjath-Babu et al., 2020), in India families affected by COVID-19 were offered doorstep grocery delivery options, etc.). In this section, the samples are analysed to get insights about the similarities and differences in the pre-COVID and during-COVID shopping patterns to aid the model formulation and interpretation.

By analysing the response from Bangladesh survey, it is found that before the outbreak half of the respondents (50% of the total respondents) did some form of remote shopping, though only half of them shopped online, while the others shopped by phone or from door-to-door vendors (Figure 2a). Further, it is interesting to note that none of the respondents was fully reliant on remote shopping for their daily necessities (i.e. no respondent mentioned about remote shopping as the main shopping method). Among the in-person shoppers, the majority of them used combinations of supermarkets, *mudir dokan* (small local grocery shops) and *katcha bazar* (local open-air markets) in a typical week before the outbreak. On the other hand, responses from the India survey (Figure 2b) revealed that almost half of the respondents (48%) used online shopping albeit only 18.5% stated it as the main shopping mode. This might be the joint effect of well-established e-commerce chains in India and the potential bias of the sample towards higher-income households. Compared to India, shopping trip frequency per week in Bangladesh was relatively higher before the pandemic (Figure 2a and Figure 2b) – potentially due to the higher number of households having domestic support-staff members (Dhar, 2018).

Moreover, in the case of in-person shopping trips made by the respondents from Bangladesh before the lockdown, active transport and rickshaw were the most frequently used mode among the ten available alternative modes. For example, more than 70% of the respondents selected active mode for shopping purpose before the outbreak, among them more than 45% used active mode 6 times a week[7] (Figure 2a). Similar statistics were also observed during the pandemic when local public transport (bus, human hauler) and ride-hailing services (RHS) were suspended nationwide (Figure 3a). On the other hand, for in-person shopping trips in India, 36% of the respondents reported using NMT with 16.5% using it as the main mode. It is closely followed by private car (34% users, with 15.5% reporting it as major one). It is also worth mentioning that similar to Bangladesh, people use NMT more frequently as compared to private cars. For example, 26% of respondents

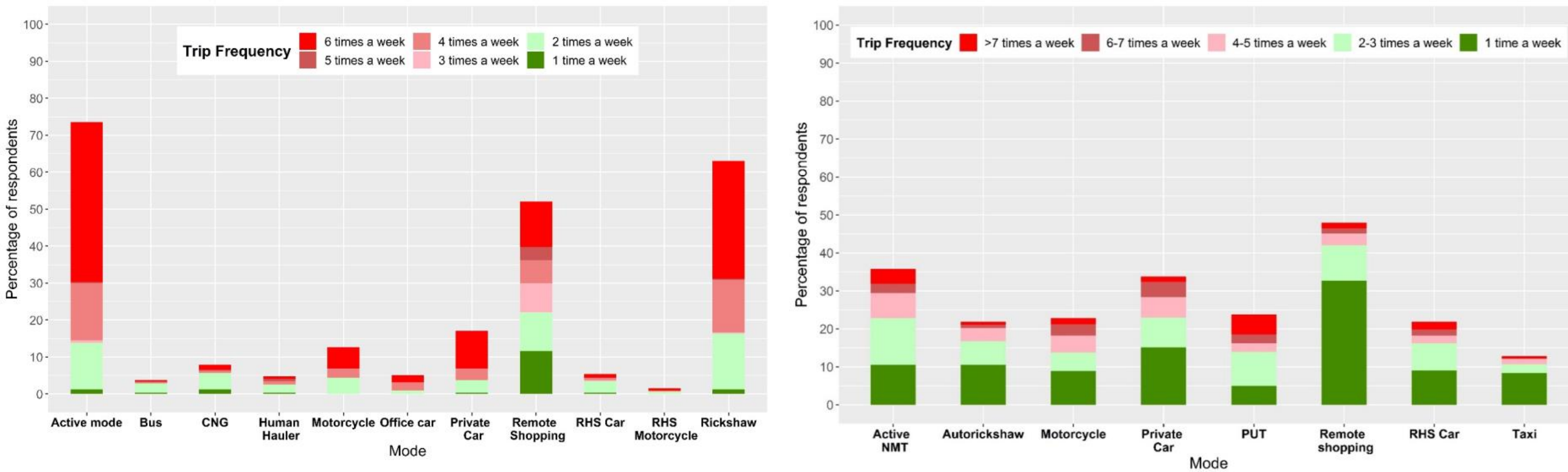
[7] It should be noted that respondents were asked to report mode choice for the outbound and return trips as separate trips in the survey

use NMT more than once a week whereas this share drops down to 19% for private car users (Figure 2b).

Since, during the lockdown Government/Non-government emergency services (e.g. hospital, bank, security services etc.) were functional in Bangladesh, use of office car[8] for shopping trips were also observed (Figure 3a). Even though autorickshaw, known as CNG in Bangladesh, were operational during the lockdown, respondents share to choose this alternative was reduced for shopping purpose. The fare of autorickshaws in Bangladesh is relatively higher compare to other available shared modes of transport (e.g. bus and human hauler), which might be a potential reason to avoid autorickshaw for the shopping trip. Overall, in-person shopping frequency had reduced in the during-COVID times in Bangladesh (Figure 3a). Among the total respondents, 31.55% used supermarket, 64.98% used Katcha Bazar, 65.30% used grocery shop, 15% used a special market developed during the lockdown. However, it can be observed that proportion of remote shopping during the lockdown slightly increased in Bangladesh from the pre-COVID time (Figure 2a and Figure 3a). Also, during the lockdown respondents from Bangladesh selected the shortest distance for a shopping trip (Figure 4a). For example, more than 50% of the respondents selected 0-1 km as their maximum travelled distance for shopping trips during the lockdown. A similar trend can be observed for India (Figure 3b) in the during-COVID days, as NMT was the most selected mode (25%) closely followed by remote shopping (24%) and private modes (18%, 13% for private car and motorcycle respectively). Interesting analogies can also be detected in changing trip length during COVID-19 outbreak as compared to normal times. For example, during COVID days more than 50% of the respondents restrict their shopping trips to a maximum distance of 3 Km relative to 26% in a normal situation (Figure 4b)[9].

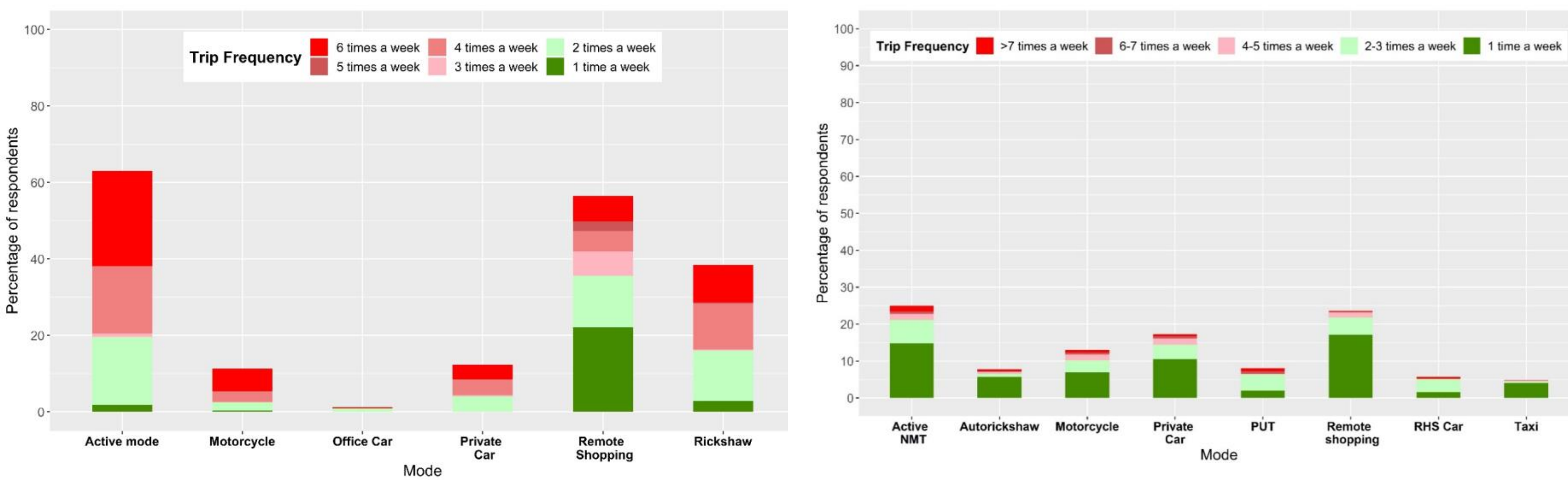
[8] In Bangladesh, it is common for many white-collar workers to have access to the car and chauffeur provided by the office as a job perk.

[9] It should be noted that the share of Indian respondents choosing not to do any shopping activity in pre-COVID and during-COVID times are 19% and 56% respectively



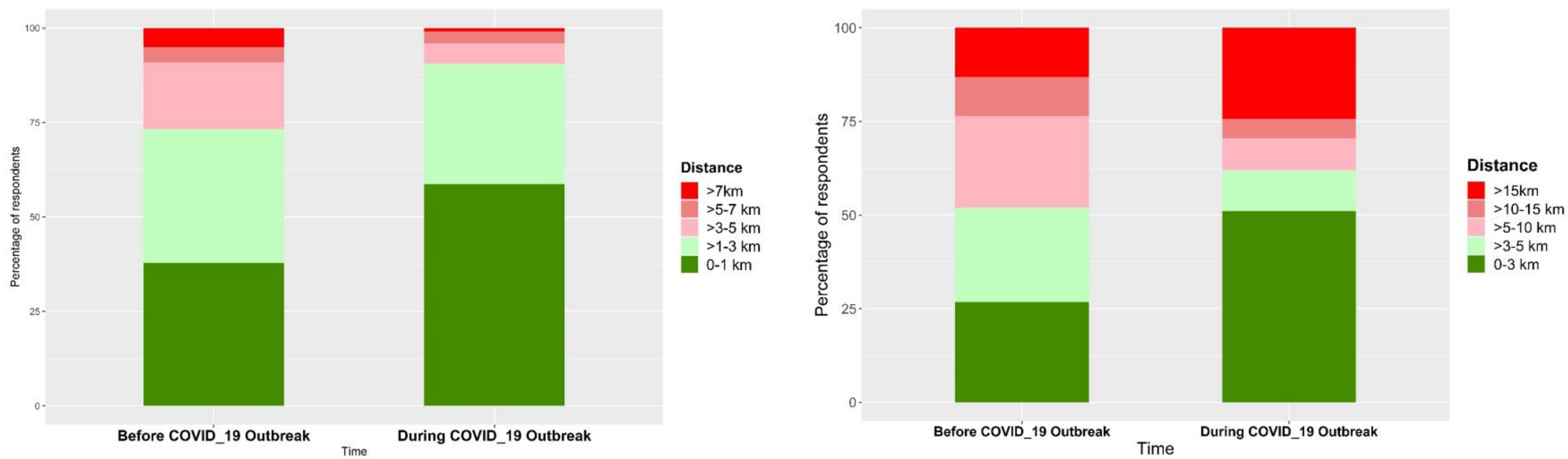

(a) Bangladesh (b) India

Figure 2: Shopping patterns in a typical week pre-COVID




(a) Bangladesh (b) India

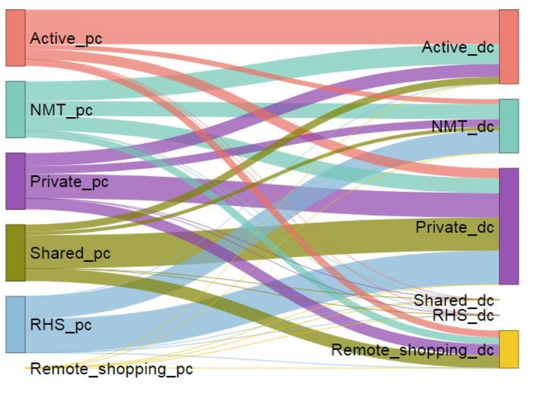
Figure 3: Mode used for in-person shopping trips during the COVID-19 outbreak



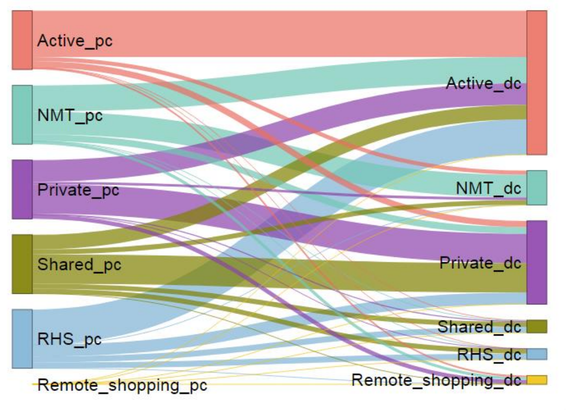

(a) Bangladesh (b) India

Figure 4: Maximum distance travelled before and during the outbreak

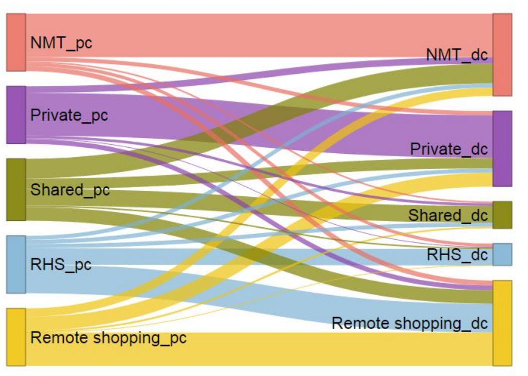
Findings of previous studies have reported that individuals have a significant propensity (referred to as *inertia* hereafter) to continue using their pre-COVID travel modes (Bhaduri et al., 2020, Shamshiripour et al., 2020). The level of inertia to retain pre-COVID mode as the major shopping mode (the mode used most frequently by an individual in a week) has hence been examined separately for RP and SP data. The potential variation between pre-COVID (referred to as "pc" in the diagram) and during-COVID (referred to as "dc" in the diagram) shopping behaviour and mode choice is shown in Figure 5.



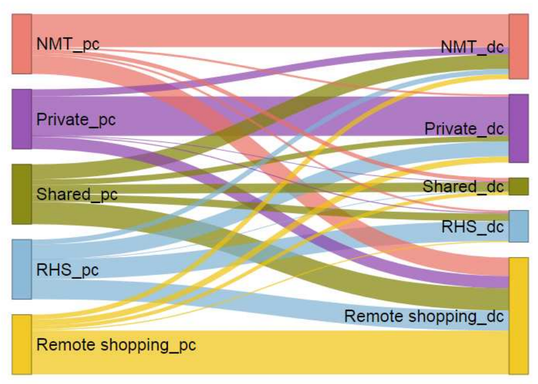

(a) RP data from Bangladesh




(b) SP data from Bangladesh




(c) RP data from India




(d) SP data from India

Figure 5: Inertia (measured in major mode switching) of different mediums

As seen in Figure 5(a), in Bangladesh, remote shopping increased in during-COVID scenario (both in the RP and SP scenarios), but not as much as in India (Figure 5(b)). This might be because of weaker e-commerce framework, s rise of fraudulent activities, poor quality of goods and refund policies and lack of a legal framework for consumer protection in Bangladesh (Irani, 2020). In the RP data, a larger share is observed to switch to private modes (private car, motorcycle and office cars), in particular from shared modes (bus, human hauler and autorickshaw) and ride-hailing services. However, in the hypothetical SP scenarios, a larger inclination to switch to active travel modes (walking and cycling) was reported – particularly from individuals who used ride-hailing services before the COVID-19 outbreak.

In the case of India, interesting similarities in inertia are observed in RP data (Figure 5(c)) where respondents show higher shares of a switch to online shopping and NMT modes (active modes and rickshaw). Notably, the majority of the respondents who were earlier using shared modes switched to NMT (as opposed to private modes). Contrary to the SP scenarios in Bangladesh, in the case of SP scenarios in India (Figure 5(d)), a larger inclination to switch to online shopping has been reported. This might be attributed to increased ease of access as well as the prevalence of remote shopping for India as compared to Bangladesh.

## 3. Model structure

Our modelling framework is based on random utility framework. Random utility theory suggests that individual decision is followed by rationality and complete information. Decision-makers choose each alternative shopping mode with the highest utility, where the utility of an alternative $i$ to a person $n$ has the form:

$$u_n(i) = u(x_{in}, s_n) \tag{1}$$

where $x_{in}$ is the vector of the attribute of alternative $i$ and for individual $n$ and $s_n$ is the vector of characteristics of the person $n$.

McFadden (1973) proposed that this utility has the linear-in-parameters separable form:

$$u(x_{in}, s_n) = V(x_{in}, s_n)\beta + \varepsilon_{in} \tag{2}$$

where $V$ is the observed component of utility, $\beta$ is the parameter vector that would be estimated using the available choice data. The unobserved variable $\varepsilon_{in}$ represents the random error term.

In this research, we have estimated joint RP-SP model. Generally, SP data has more noise than RP data. As proposed by (Ben-Akiva and Morikawa, 1990), the difference between the error terms in RP and SP can be presented as a function of the variances of each type of error:

$$\sigma_{RP}^2 = \mu^2 \sigma_{SP}^2 \tag{3}$$

Where, $\mu$ is the scale coefficient.

After adopting the formulation for RP and SP data the utility equation can be written as follows:

$$u^{RP}({x_{in}}^{RP}, s_n) = V^{RP}({x_{in}}^{RP}, s_n)\beta + {\varepsilon_{in}}^{RP} \tag{4}$$

$$\mu * u^{SP}({x_{in}}^{SP}, s_n) = \mu * (V^{SP}({x_{in}}^{SP}, s_n)\beta + {\varepsilon_{in}}^{SP}) \tag{5}$$

Multinomial logit (MNL) model, which is based on the assumption that the error term $\varepsilon_{in}$ is independently and identically distributed (IID), has been widely used for different choice experiments e.g. mode choice, destination choice, vehicular ownership etc. However, in this case, in-person shopping alternatives and passive shopping alternatives are likely to have unobserved correlations in the error terms. Therefore, instead of MNL model, we used a Nested Logit (NL) formulation where correlations are allowed among alternatives (Hensher et al., 2008). Figure 6 shows the shopping choice alternatives and nests[10].

[10] Other nesting structures were also tested but this one had the best performance in terms of goodness-of-fit and coefficient values

Here, the probability for alternative $i$ in the nest $S_m$ for the joint model:

$$P_i = P_{S_m} P_{i|S_m} \tag{6}$$

$$P_{S_m} = \frac{e^{\lambda_m I_m}}{\sum_{m=1}^{M} e^{\lambda_I I_I}} \tag{7}$$

The conditional probability of a respondent choosing alternative $i$ for RP and SP data would be:

$$P_n(i, RP|S_m) = \frac{e^{\frac{V_{n,i}{}^{RP}}{\lambda_m}}}{\sum_{j=1}^{J_{RP \epsilon S_m}} e^{\frac{V_{n,j}}{\lambda_m}}} \tag{8}$$

and,

$$I_m{}^{RP} = ln \sum_{j_{RP \epsilon S_m}} e^{\frac{V_{n,i}{}^{RP}}{\lambda_m}} \tag{9}$$

$$P_n(i, SP|S_m) = \frac{e^{\mu \frac{V_{n,i}{}^{SP}}{\lambda_m}}}{\sum_{j=1}^{J_{SP \epsilon |S_m}} e^{\mu \frac{V_{n,j}}{\lambda_m}}} \tag{10}$$

and,

$$I_m{}^{SP} = ln \sum_{j_{SP \epsilon S_m}} e^{\frac{V_{n,i}{}^{SP}}{\lambda_m}} \tag{11}$$

where the vector of the error term $\varepsilon$ has the following cumulative distribution:

$$F\left(\varepsilon_{n,j}\right) = e^{-(\sum_{m=1}^{M}\left(\sum_{j \epsilon S_m} e^{-\frac{\varepsilon_j}{\lambda_m}}\right)^{\lambda_m})} \tag{12}$$

The coefficients of the NL model are estimated using the maximum likelihood technique using the software Apollo (Hess and Palma, 2019).

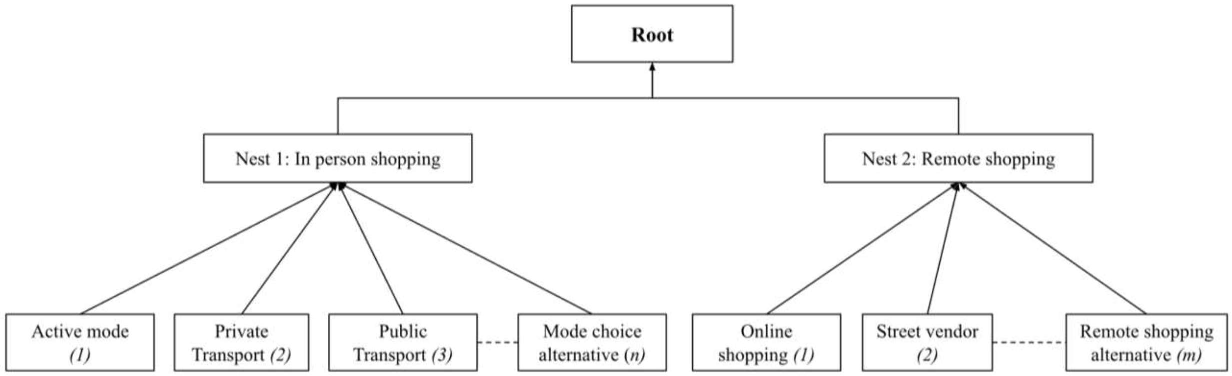



Figure 6: Nesting structure of shopping choice alternatives

## 4. Joint RP-SP model estimation results

The model comprises of three types of independent variables: household-specific variables (income, vehicle ownership), pre-COVID behaviour related variables (pre-COVID frequency of using the mode in a week and whether or not it was the main mode, pre-COVID maximum distance travelled), and current COVID-19 scenario-specific variables (number of cases and deaths in the country, number of cases in the division/state, number of family members currently affected by COVID-19 if any). Both generic and RP/SP specific coefficients have been tested for the contextual variables and the inertia variables. In some cases, for the ease of comparison and interpretation, the coefficients have been retained despite being statistically insignificant. The estimation results of the joint RP-SP nested logit models for each country (on the weight-adjusted data) are presented in Table 3[11].

[11] The model without the weight adjustment yielded quite similar parameters and have been presented in Appendix A

Table 3: NL model combing SP and RP data

| | | | | | | |
|---|---|---|---|---|---|---|
| *Model details* | | | | | | |
| Number of observations | 951 | | | 1330 | | |
| Number of individuals | 317 | | | 609 | | |
| Parameters | Bangladesh | | | India | | |
| | Estimate | Robust *t*-stat | Sig. | Estimate | Robust *t*-stat | Sig. |
| Alternative Specific Constants (ASCs) | | | | | | |
| Remote shopping *(base)* | 0.00 | - | | 0.00 | - | |
| Active mode | 1.75264 | 7.19 | *** | n/a | n/a | |
| Non-motorized transport (NMT) | n/a | n/a | | -0.9924 | -3.17 | *** |
| Rickshaw | 1.24242 | 4.49 | *** | n/a | n/a | |
| Car | 0.72486 | 3.06 | *** | -2.5893 | -4.07 | *** |
| Office transport | -0.19192 | -0.58 | | n/a | n/a | |
| Motorcycle | 0.62770 | 2.38 | ** | -1.9104 | -3.96 | *** |
| Auto-rickshaw | -1.27802 | -2.13 | ** | -2.5929 | -3.38 | *** |
| Taxi | n/a | n/a | | -2.6006 | -3.36 | *** |
| Ride-hailing services (Car) | -2.18341 | -2.38 | ** | -2.0358 | -3.41 | *** |
| Ride-hailing services (Motorcycle) | -1.55463 | -2.47 | ** | | | |
| Public transport/ Bus | -1.17052 | -2.00 | ** | -2.3179 | -3.13 | *** |
| Human hauler | -0.79651 | -1.69 | * | | | |
| Pre-COVID behaviour variables | | | | | | |
| *Pre-COVID frequency of using the alternative* | | | | | | |
| Generic for RP and SP | 0.03886 | 2.31 | ** | 0.2014 | 2.14 | ** |
| *Pre-COVID main mode* | | | | | | |
| SP-specific | 0.51462 | 3.96 | *** | 0.7488 | 2.05 | ** |
| RP-specific | 0.34396 | 2.68 | *** | 0.9654 | 2.69 | *** |
| *Pre-COVID maximum distance travelled* | | | | | | |
| Active mode | -0.16194 | -2.44 | ** | - | - | |
| Remote shopping | - | - | | 0.1679 | 0.86 | |
| Socio-demographic variables | | | | | | |
| *Car ownership* | | | | | | |
| Rickshaw/NMT | -0.34064 | -1.90 | * | -0.0791 | -0.27 | |
| *Motorcycle ownership* | | | | | | |
| Active mode | -0.27414 | -2.04 | ** | - | - | |
| Rickshaw/NMT | -0.55668 | -2.22 | ** | -0.7976 | -1.53 | |
| Ride-hailing services | 0.73307 | 3.00 | *** | -0.3695 | -0.62 | |

| Parameters | Bangladesh | | | India | | |
|---|---|---|---|---|---|---|
| | Estimate | Robust *t*-stat | Sig. | Estimate | Robust *t*-stat | Sig. |
| *Income* | | | | | | |
| High-income dummy[a] for Car | 0.64795 | 3.51 | *** | 1.1087 | 2.33 | ** |
| High-income dummy[a] for Remote shopping | 0.65236 | 3.01 | *** | 0.0857 | 0.43 | |
| Contextual variables | | | | | | |
| *Number of people affected in country* | | | | | | |
| Private mode | 0.16575 | 2.56 | ** | 0.2176 | 2.16 | ** |
| *Number of deaths at division/ state level* | | | | | | |
| Non-motorized transport | - | - | | 0.2327 | 2.15 | ** |
| Remote shopping | 0.28727 | 2.54 | ** | - | - | |
| *Number of people affected in the household* | | | | | | |
| Rickshaw | 0.36197 | -2.17 | ** | - | - | |
| Remote shopping | -0.52810 | -2.65 | *** | 0.3763 | 1.51 | |
| *Government restriction* | | | | | | |
| Remote shopping | 0.45956 | 2.00 | ** | 0.1965 | 1.39 | |
| Scale variables | | | | | | |
| mu_RP | 1 | - | | 1 | - | |
| mu_SP | 1.86796 | 6.07 | *** | 1.2692 | 3.64 | *** |
| lambda_inperson | 0.55983 | 6.01 | *** | 0.7397 | 3.02 | *** |
| LL(0, whole model) | -386.445 | | | -2765.66 | | |
| LL(final, whole model) | -188.809 | | | -238.504 | | |
| Rho-square (0) | 0.5114 | | | 0.9138 | | |
| Adj.Rho-square (0) | 0.439 | | | 0.9054 | | |
| AIC | 433.62 | | | 523.01 | | |
| BIC | 569.63 | | | 642.45 | | |
| Estimated parameters | 28 | | | 23 | | |

*** 99% significance level, ** 95% significance level, * 90% significance level

[a] The high-income group corresponds to individuals from households with high monthly income (more than 75K and 100K BDT in a month respectively for India and Bangladesh)

The first section of Table 3 includes the alternative-specific constants (ASCs) for in-person and remote shopping activities, where remote shopping is used as a base. For Bangladesh, values of the ASCs indicate that all else being equal, the utility of in-person shopping by active mode, rickshaw and private modes are higher than that of remote shopping as well as in-person shopping by shared (Bus and human haulers) or ride-hailing services (car or motorcycle based). As noted in Section 2.3 (Figures 2 and 3) in Bangladesh, the in-person shopping frequencies per week is higher both before the pandemic and during the pandemic indicating reliance on multiple channels (such as Mudir dokan, Katcha Bazar, supermarket, grocery shop etc.). This is an indication that their shopping needs are diverse and cannot be fully substituted by remote shopping. In the case of

India, all else being equal, remote shopping is observed to have the highest utility. For the other modes, a somewhat similar order of magnitude of the ASCs is observed in both countries. For instance, the in-person shopping modes of non-motorized transport (NMT) and private modes (except cars) have higher utility than the shared modes. However, unlike Bangladesh, all else being equal, ride-hailing services have higher utility than shared modes in India.

Three variables have been used to capture the effects of pre-COVID shopping behaviour on the during-COVID choices: the frequency of using each alternative, the primary means of shopping (used as a dummy variable in the utility of the associated alternative) and the maximum distance travelled for a shopping trip before the pandemic (January 2020). The coefficient of the pre-COVID frequency indicates that the propensity to choose any alternative is higher if the frequency of using it was higher during pre-COVID. The coefficient of the main mode captures the additional propensity to continue using the modes which had been the main mode in pre-COVID days – though this was significantly different between the RP and the SP. The coefficient of the pre-COVID maximum distance reveals that those who were travelling a long distance before the pandemic are less likely to do in-person shopping by active mode during-COVID. This may be driven by the fact that travelling long distances essentially leads to increased exposure in COVID infected surroundings which can be avoided in case of remote shopping as it has minimum person-to-person contact. In the case of India, this is explained by the positive coefficient for remote shopping, though the effect is not statistically different from zero.

Further, from the model estimates, a significant difference is observed depending on the income and types of vehicles owned by a household. For Bangladesh, it can be seen that those who are car owners (23% of the total respondents) are less likely to choose rickshaw for in-person shopping trips in the during-COVID times compared to remote shopping or any other alternative modes available for the shopping trip. Also, in India, a negative propensity towards NMT is observed. Its lack of statistical insignificance can be linked to the infrequent use of a private car for shopping trips in COVID scenarios (refer to Figure 3b). In terms of motorcycle ownership, in Bangladesh households who own motorcycles are less likely to use both active mode and rickshaw, and more likely to use ride-hailing services, if available, during the pandemic. Similar propensities are observed for India too, except for ride-hailing services for which the effect is not statistically different from zero.

The association between the household income of the respondents and higher propensity to private modes and remote shopping is intuitive. In both countries, high-income households have a significant positive propensity for using cars for shopping trips. Interestingly, for India, the high-income people do not have a significant additional preference for remote shopping in comparison with the other income groups. The statistical insignificance is likely to be linked to a greater penetration level of e-commerce activities in various socioeconomic strata of Indian society. The income effects have also been tested for other alternative modes which are not significantly different than zero for either country and therefore removed from the final model.

Finally, the effects of different during-COVID contextual attributes have been explored. Three categories of contextual attributes have been considered for the model estimation: number of people affected at the country level, number of deaths at the division or state level, number of COVID affected people at the household level. Further, the imposition of Government restrictions has been considered to understand during-COVID shopping behaviour. Most of these contextual attributes are statistically significant for both countries. For both Bangladesh and India, if the number of COVID affected people increase at the country level, people are more likely to choose privately owned vehicles. Furthermore, in Bangladesh, if the number of deaths increases at the division/state level people are more likely to choose remote shopping compared to in-person shopping. Although in the Indian context, respondents prefer NMT as opposed to other modes. This might be explained as a combined effect of partial restrictions on e-commerce services and the larger proclivity of respondents to carry out more local trips on foot or by bicycle due to time-flexibility gained from work-from-home. Also, for both the countries from the SP scenario it is clear that if there are Government restrictions on people's movement, they are more likely to choose remote shopping. However, for Bangladesh, if there are COVID affected people at the household level then they are less likely to choose remote shopping or rickshaw compared to other alternatives available for in-person shopping. The trend is little different for India as people depend more on remote shopping which might be attributed to different lockdown norms in India where if any one of household members was detected with COVID, district administrations were imposing quarantine for all other members too. As a result, the household has to depend on essential online services provided by district administration. But that has not been the case in Bangladesh.

The scale coefficients corresponding to the SP and the nesting structure support the joint RP-SP NL models.

## 5. Directions of Future Research

The data used in this paper is limited to urban areas. The changes in shopping behaviour in rural areas is expected to be substantially different. It will be interesting to apply a similar model for rural areas as well if suitable data is available. However, the choice set of shopping modes is very small and there is no provision of online shopping. Further, the majority of the inhabitants of the rural areas are captive to specific transport modes. Hence, the extent of switching shopping modes due to Covid-19 is expected to be very small in these areas.

Further, the RP data used in the research involved recalling past behaviour. Combining the survey data with large-scale passive data (e.g. online sales records, mobile phone traces, etc.), which have a better representation of travel behaviour of the mass population, but typically lack socio-demographic information, may help in accounting for the potential biases due to the recall.

On the other hand, the preference for shopping modes can be significantly affected by attitudes and perceptions of the respondents as well as their risk-taking propensity. Although such information was collected on a limited scale in this survey, it has not been incorporated in the present study due to the limited sample size and lack of clear trends. It would have been also good to include impact of different types of social-distancing rules in public transport modes and public spaces in the SP scenarios (e.g. use of masks, enforcement of capacity limits, etc.). But these attributes may have been difficult to comprehend in an online survey and could have made the choice tasks more complex and led to response fatigue.

Further, the focus of the current research is the choice of the main shopping mode. Accommodating the discrete-continuous nature of the choices (shopping mode and frequency) by testing Multiple Discrete-Continuous Nested Extreme Value (MDCNEV) and mixed MDCEVs are also interesting directions for future research.

## 6. Concluding words

In this research, the shopping behaviour has been analyzed in two temporal and spatial dimensions (pre-COVID and during-COVID, Bangladesh and India). The objective was to assess the impact of COVID-19 pandemic on the weekly shopping habit for daily necessities. The effects on the choice of main shopping mode have been estimated with a comprehensive array of NL modes with different nests for remote and in-person alternatives. Using SP data enabled us to test the sensitivity to different contextual factors. Combining it with RP data enabled us to adjust the scale difference in SP and accounted for the potential hypothetical bias and/or behavioural incongruence (which could have affected the reliability of the findings (e.g. Auld et al. (2012)).

The estimation results reflect the different shopping preference of various socio-economic groups. In Bangladesh, high household income and vehicle ownership play an important role in the selection of shopping mode during-COVID. Those who own a car and have higher household income might have a high level of concern and put more emphasis on precautionary measures related to the pandemic, hence, show higher propensity to use remote shopping to reduce the chance of infection. However, having motorcycle ownership does not indicate any additional pandemic related precautions and as such, households owning motorcycles show less propensity to switch to remote shopping compared to ride-hailing services. This result complies with the finding from Abdullah et al. (2020).This result complies with the finding from Abdullah et al. (2020). Such risk-taking attitudes are a critical factor in predicting human mobility in the event of infectious diseases (Chan et al., 2020). On the other hand, in India vehicle ownership does not have a significant influence on shopping mode choice behaviour during the pandemic. The reason could be the already high preference of all groups to do online shopping. The study also sheds light on the fact that unlike Bangladesh higher household income is not a decisive factor for remote shopping in India which might well be attributed to greater penetration of e-commerce chains (both national and international) in the Indian market.

Moreover, the present study shows interesting similarities as well as differences in sensitivities towards contextual variables. Some of the contextual variables seem to have a significant impact on shopping preference in both countries such as the number of affected people at the country level and the number of deaths at the division or state level. This demonstrates that there are substantial self-awareness of COVID-19 risks and people are likely to 'spontaneously' adjust their shopping behaviour considering the COVID situation of their surroundings. This is in agreement with the findings of Bhaduri et al. (2020).This is in agreement with the findings of Bhaduri et al. (2020). However, in India people tend to adjust their shopping behaviour irrespective of the government restrictions or whether or not there are infected household members. Overall, these findings signify that 'one size does not fit all countries' and different levels of interventions and/or restrictive measures may be required in each country to achieve the desired level of reduction of in-person travel to control the spread of the virus. It is interesting to note that, in the case of Bangladesh, results indicate that having an infected member in the household may not deter the other members to use NMT and does not spontaneously encourage the household to shift to online shopping. This supports the notion that the reduction of in-person shopping trips would not be possible without improving the technology adaptation and reliability of the remote shopping options (in addition to restrictive measures). This, coupled with the finding regarding the presence of strong inertia to continue using the pre-COVID modes, indicate the need for active intervention strategies to nudge households, particularly those owning motorcycles, to COVID-safer alternatives. The insights will hence be useful to planners and policymakers for predicting the shopping modes in different future scenarios and formulating effective restriction and other measures to ensure safety (e.g. measures to make ride-hailing services more COVID-safe, developing logistic and legal frameworks to improve the reliability of online shopping, etc.).

The limited similarity of the model parameters between two countries with similar socio-cultural fabric indicates that direct transferability of policies among countries is not likely to be highly effective.

On a broader level, the research demonstrates that joint RP-SP models can be used to develop behaviourally intuitive and statistically robust models in the context of pandemics which can be deployed to predict the extent of behavioural shifts in potential future policy scenarios.

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**Appendix- A**

The final model presented in Table 3 refers to the estimated coefficients of the weighted model (in terms of household income) to improve the representativeness of the result. The addition of weightage has improved the model log-likelihood and subsequently the goodness-of-fit (measured by adjusted rho-square). It is worth mentioning that the effect is more prominent for India as compared to Bangladesh. We might relate such instance to *deterministic nature* of mode choices of *low household income* group. This particular group is the majority of urban population (more so in India), hence, putting higher weightage results in increasing log-likelihood values. The estimated coefficients of the unweighted sample are presented below.

Table 4A: NL model combing SP and RP data **(without weight)**

| | | | | | | |
|---|---|---|---|---|---|---|
| *Model details* | | | | | | |
| Number of observations | | 951 | | | 1330 | |
| Number of individuals | | 317 | | | 609 | |
| Parameters | Bangladesh | | | India | | |
| | Estimate | Robust *t*-stat | Sig. | Estimate | Robust *t*-stat | Sig. |
| Alternative Specific Constants (ASCs) | | | | | | |
| Remote shopping *(base)* | 0.00 | - | | 0.00 | - | |
| Active mode | 1.6847 | 7.41 | *** | | | |
| Non-motorized transport | | | | -0.9452 | -6.81 | *** |
| Rickshaw | 1.0712 | 4.70 | *** | | | |
| Car | 0.7140 | 3.06 | *** | -1.8499 | -7.37 | *** |
| Office transport | -0.1753 | -0.54 | | | | |
| Motorcycle | 0.5339 | 2.18 | ** | -1.4471 | -7.54 | *** |
| Auto-rickshaw | -1.1888 | -2.01 | ** | -2.4421 | -6.02 | *** |
| Taxi | | | | -2.7191 | -5.94 | *** |
| Ride hailing services (Car) | -2.0828 | -2.30 | ** | -1.8765 | -5.82 | *** |
| Ride hailing services (Motorcycle) | -1.4680 | -2.38 | *** | | | |
| Public transport/ Bus | -1.1904 | -2.01 | ** | -2.4472 | -6.58 | *** |
| Human hauler | -0.7404 | -1.67 | * | | | |
| Inertia variables | | | | | | |
| *Pre-COVID frequency of using the alternative* | | | | | | |
| RP and SP | 0.0491 | 4.25 | *** | 0.1961 | 4.35 | *** |
| *Pre-COVID main mode* | | | | | | |
| SP | 0.4423 | 3.92 | *** | 0.3925 | 3.09 | *** |
| RP | 0.2307 | 2.30 | ** | 0.7845 | 5.42 | *** |
| *Pre-COVID maximum distance travelled* | | | | | | |
| Active mode | -0.1252 | -2.28 | ** | - | - | |

| | | | | | | |
|---|---|---|---|---|---|---|
| Remote shopping | - | - | | - | - | |
| Socio-demographic variables | | | | | | |
| *Car ownership* | | | | | | |
| Non-motorized transport | | | | - | - | |
| Rickshaw | -0.2188 | -1.51 | *** | | | |
| *Motorcycle ownership* | | | | | | |
| Active mode | -0.4058 | -3.38 | *** | | | |
| Non-motorized transport | | | | -0.5619 | -3.23 | *** |
| Rickshaw | -0.6091 | -2.59 | *** | | | |
| Shared mode | 0.2788 | 1.19 | | 0.2056 | 1.07 | |
| Ride hailing services | 0.8015 | 3.17 | *** | -0.0165 | -0.07 | |
| *Income* | | | | | | |
| High income dummy[a] for Car | 0.5933 | 3.60 | *** | 0.5392 | 2.82 | *** |
| High income dummy[a] for Remote shopping | 0.5788 | 2.75 | *** | 0.0828 | 0.67 | |
| Contextual variables | | | | | | |
| *Number of people affected in country* | | | | | | |
| Private mode | 0.1845 | 3.25 | *** | 0.0251 | 0.42 | |
| *Number of deaths at division/ state level* | | | | | | |
| Non-motorized transport | - | - | | 0.0605 | 1.96 | ** |
| Remote shopping | 0.2321 | 2.10 | ** | - | - | |
| *Number of people affected at household level* | | | | | | |
| Rickshaw | -0.2225 | -1.87 | * | | | |
| Remote shopping | -0.4357 | -2.34 | *** | 0.0767 | 0.78 | |
| *Government restriction* | | | | | | |
| Remote shopping | 0.5021 | 2.24 | ** | 0.0911 | 1.63 | |
| Scale variables | | | | | | |
| mu_RP | 1 | - | | 1 | - | |
| mu_SP | 1.8936 | 6.27 | *** | 1.7666 | 6.36 | *** |
| lambda_inperson | 0.5271 | 6.33 | *** | 0.5197 | 5.69 | *** |
| LL(0, whole model) | -2280.39 | | | -2765.66 | | |
| LL(final, whole model) | -1133.62 | | | -1072.77 | | |
| Rho-square (0) | 0.5029 | | | 0.6121 | | |
| Adj.Rho-square (0) | 0.4906 | | | 0.6045 | | |
| AIC | 2323.24 | | | 2187.54 | | |
| BIC | 2459.25 | | | 2296.59 | | |
| Estimated parameters | 28 | | | 21 | | |

*** 99% significance level, ** 95% significance level, * 90% significance level

**Appendix- B**

**Details of the Stated Preference (SP) Survey**

After completing the RP part of the questionnaire, each respondent was presented with two SP scenarios each. In each scenario, they were presented with different hypothetical contexts featuring the COVID-19 situation in the country, city and family along with the type of Government restriction in place. The presented attributes (5) and the number of levels (3 each) are presented in Table B1.

**Table B1: Example of SP levels**

**(a) India**

| **Attribute** | **Number of Levels** | **Levels** |
|---|---|---|
| Number of cases in the country | 3 | 750, 2000, 10000* |
| Number of cases in the city | 3 | 5%, 10%, 15%<br>(of the number of cases in the country) |
| Number of deaths in the city | 3 | 1%, 2%, 5%<br>(of number affected in the city) |
| Number of affected household members | 3 | 0,1,2 |
| Type of Government restriction | 4 | No lockdown[1], Semi lockdown[2], Relaxed lockdown[3], Full lockdown[4] |

* Replaced by 3000, 10000, 25000 on the last week as the actual number of affected people soared more than initially expected

[1]Social distancing (No lockdown) - Institutions closed / WFH encouraged/ Mass gatherings discouraged

[2]Semi-lockdown - Office+Schools closed/ Night curfew imposed/ Limited movement allowed other than essential ones

[3]Relaxed lockdown - Limited public transport services operate as well as essential services like food, medicine, bank are allowed for restricted duration (say 12 hrs/ day)

[4]Full-lockdown- ONLY essential services like food, medicine, bank are allowed and that too for highly restricted duration (say 6 hrs/ day)

**(b) Bangladesh**

| **Attribute** | **Number of Levels** | **Levels** |
|---|---|---|
| Number of cases in the country | 3 | 2000, 4000, 10000 |
| Number of cases in the city | 3 | 30%, 40%, 50%<br>(of the number of cases in the country) |
| Number of deaths in the city | 3 | 1%, 2%, 5%<br>(of number affected in the city) |

| | | |
|---|---|---|
| Number of affected household members | 3 | 0,1,2 |
| Type of Government restriction | 4 | No lockdown, Full lockdown |

Overall, 12 SP scenarios were developed each time based on D-optimal design of which 2 were dominant scenarios and were removed. The participants were allocated two randomly chosen scenarios and asked to select their shopping behaviour in each scenario.

An example SP scenario for Bangladesh has been presented below. The full questionnaires for both countries can be downloaded from https://tinyurl.com/pi0oj3sj
(DOI: 10.13140/RG.2.2.24070.70727)

**Figure B1: Sample of SP survey used for Bangladesh (translated from Bengali)**

We would now like to present you with two future probable scenarios of COVID Outbreak. Please think carefully and let us know what will be your shopping choices in these scenarios.

**FUTURE SCENARIO A:**

IMAGINE A FUTURE SITUATION:

*Number of cases in the country:* **2000**
*Number of confirmed active cases in your city:* **800**
*Number of deaths in your city in the past week*: **40**
*Number of your household members with COVID like symptoms* (dry cough, fever): **2**
*Government advisory:* **Schools closed, Working from home encouraged, Mass gatherings discouraged**

1. In the situation described, how many times would YOU OR ANY MEMBER OF YOUR HOUSEHOLD visit market in-person (going physically) PER WEEK? *

| | | | |
|---|---|---|---|
| Never | 1 time | 2 times | 3 times |
| 4 times | 5 times | 6 times | 7 times or more |

2. In the situation described, WHAT VEHICLES would YOU OR ANY MEMBER OF YOUR HOUSEHOLD use to visit market PER WEEK and how often? For example, if you go from home to the shopping mall in a rickshaw and return by Uber, that will count as 1 trip in rickshaw, 1 trip in Uber; if you use Uber both ways, that will count as 2 trips by Uber. If you WILL NOT use a particular mode (e.g. Bus), leave the row (for Bus) BLANK.

| | 1 time | 2 times | 3 times | 4 times | 5 times | > 5 times |
|---|---|---|---|---|---|---|
| Walk/ Bicycle | | | | | | |
| Rickshaw | | | | | | |
| Private car | | | | | | |
| Office car/ Microbus | | | | | | |
| Motorcycle | | | | | | |
| Tempo/ Human hauler | | | | | | |
| Ride Hailing Service (Uber/ Pathao car) | | | | | | |
| Ride Hailing Service (Uber/ Pathao motorcycle) | | | | | | |
| Bus | | | | | | |
| CNG | | | | | | |

3. In the situation described, if YOU OR ANY MEMBER OF YOUR HOUSEHOLD plan to use any option more than 6 times then please specify which mode and how many times?
4. In the situation described, what is the distance YOU OR ANY MEMBER OF YOUR HOUSEHOLD would travel for the longest of trips to the market?

| | | | |
|---|---|---|---|
| No travel | 0-1 Km | >1 -3 Km | >3 -5 Km |
| >5 -7 Km | >7 Km | I do not know | |

5. In the situation described, what is the maximum amount of time YOU OR ANY MEMBER OF YOUR HOUSEHOLD would spend on the market?

| | | | |
|---|---|---|---|
| 0 minute | 15 minutes | 30 minutes | 45 minutes |
| 60 minutes | 1-2 hours | 2-3 hours | >3 hours |

6. If YOU OR ANY MEMBER OF YOUR HOUSEHOLD is not interested in going to the market in-person the situation described, how do you buy the essentials?
   a. Buy from online market (e.g. Pathao Food, Daraj, Bikroy.com etc.)
   b. I will buy it from a known shop by telephone
   c. I will ask neighbours, friends, relatives for help
   d. I will buy it from the street hawkers
   e. I will bring it from our native house
   f. Others