Equity Focused Assessment of Secondary Effects of COVID-19 on Families and Children in Nepal

An end line report

ENDLINE SURVEY REPORT: ALL ROUNDS

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Executive Summary

This end line report makes use of the panel data structure of UNICEF's CFT (Child and Family Tracker) to provide additional insight into certain key outcomes and identify key correlations. It is meant to be a companion to a) the base line report and b) CFT power point reports for all the rounds. While the CFT reports for each round reported on all the variables appearing in those rounds, this end line report focuses on variables that consistently appeared across all the rounds using the sample of individuals who responded across all the rounds. The final CFT power point report already presented comprehensive time series of all the variables possible. This report probes deeper into select key outcomes and identifies variables that were important in explaining variations across time, within respondents and between respondents.

The report begins with a description of the sample including sample loss over the rounds. It then examines some basic background characteristics that were deemed important in influencing outcomes. Key outcomes identified during each round were income distributions, probability of jobs/livelihood losses, reduced dietary intake of children, households declaring food as an immediate need, frequency of breastfeeding, witnessing violence against women and children and children not studying. In addition, since outcomes are influenced by coping strategies (and vice versa) this end-line report also presents a panel data analysis of coping strategies used by respondents through the 6 rounds (Annex). The key findings suggest that incomes and job losses along with coping strategies were highly significant in explaining outcomes – not only at each point in time, but also through time. Another key finding is that recovery has been uneven for these outcomes.

Finally, the end line report summarizes some of the key findings on health, nutrition, Public Health Safety Measures (PHSM) behaviour and child labour from all six rounds. The data suggest an increasing preference for private hospitals though this is driven by income and geography. A worrisome finding is the low rate of breast feeding normally and a significant number of respondents worrying their children were becoming too thin. This report is also able to compare safety measures adopted by households prior to the lockdown being lifted to the period when lockdown was lifted and found a large decrease in the share of respondents staying at home after the lockdown. The results also confirm that respondents who reported their children were working for income also suffered multiple other deprivations including being from low income households to begin with.

In the annex, standard panel data techniques are used to examine key outcomes from a panel data perspective where individual outcomes could be correlated across time. An important contribution of this end line report is to use standard panel data regression framework to examine how these key outcomes moved over time, were affected by lockdown, and how they varied between and within individuals. In particular both fixed effects (within sample variation) as well as random effects (between individual variation) models were used to isolate the key outcomes allowing for the possibility that outcomes could be correlated to each other.

The panel data framework is followed by an enquiry into the number of times respondents reported shocks. The results are equally sobering. Significant number of respondents reported multiple shocks in incomes, job losses, reducing dietary intake for children, struggling for food and witnessing violence against women and children. These ‘count’ variables were also influenced by coping strategies, geography, receipt of social security allowances and other background variables such as disability status.

The data analyses suggest that children suffered through the Covid-19 pandemic in numerous and overlapping ways – not the least obvious being the enormous losses in education. In addition, a significant number of children were exposed to their families’ losing jobs, livelihoods, or incomes. This report is also able to highlight reductions in children’s dietary intake as an adverse coping mechanism affecting large numbers of children. At the same time the data uncovers evidence of children facing increasing psychosocial burdens associated with exposure to violence and anger or aggression. Finally, the uneven recovery suggested by the data suggest that broad based and urgent measures are needed to reverse the impact of multiple shocks experienced in multiple dimensions of children’s lives.

Description of the sample and timings of the survey:

The baseline sample comprised of 7,655 respondents covering more than 80% of all municipalities. The primary sampling was done using a geospatial grid sampling approach mapped to telephone numbers from the Sharecast Initiative Nepal (SCIN, Nepal based partner/research firm) phone number database. This database of phone numbers was already selected based on an approximate Probability Proportional to Size technique. In the secondary stage of sampling, purposive sampling was used to reach 7,655 respondents who had children living with them. The first (baseline or wave 0) household roster revealed a total of 42,400 individuals among whom 38% where children.

The CFT was conducted over 6 waves or rounds and was designed as a panel data survey – the same households were contacted repeatedly through the rounds. However, not all 7,655 participants participated through all 6 waves. Furthermore, due to the dynamic nature of the survey, some questions appeared only in certain waves, while a few questions were retained through all 6 waves (Table 1).

Table 1: Distribution of sample across waves

Wave/Round	Dates	Sample Size	# Variables
0	17 May to 30 May 2020	7655	332
1	01 July to 11 Jul 2020	6521	422
2	11 Aug to 20 Aug 2020	6675	310
3	29 Sep to 06 Oct 2020	6588	418
4	21 Dec to 31 Dec 2020	6384	459
5	26 Jan to 05 Feb 2021	6313	622

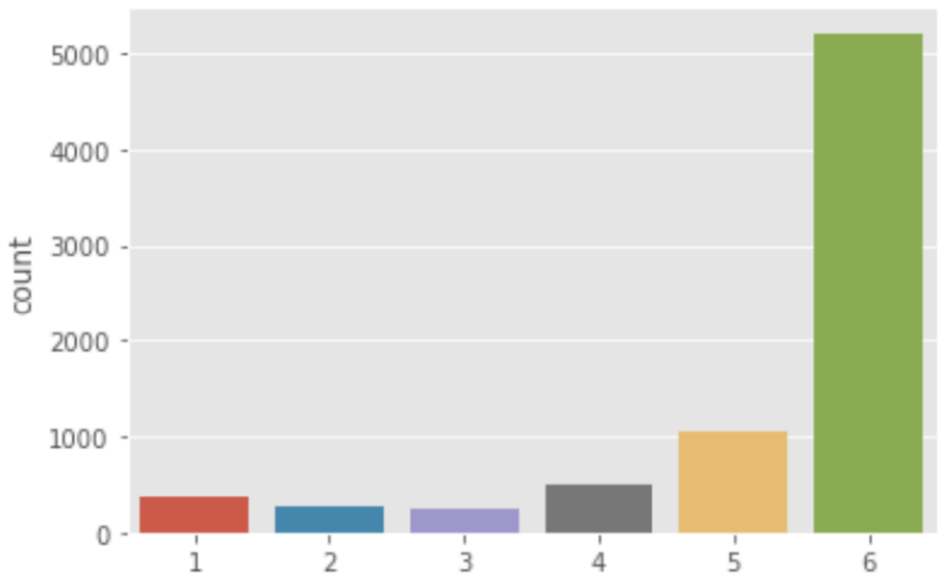


Figure 1: Frequency of respondents' participation across waves

Out of an initial sample size of 7,655 respondents who participated in the baseline, 5,208 completed all 6 waves/rounds of the survey (Figure 1). This means a sample loss of approximately 32% through the rounds. Another 1,039 respondents participated in 5 rounds, 501 respondents participated in 4 rounds, 258 respondents participated in only 3 rounds, 266 respondents participated in only 2 rounds while 383 respondents participated in only 1 round.

The reasons for the sample loss can be attributed to a) fatigue and length of the interview b) seasonal factors such as harvest making it difficult to reach respondents through all waves c) movement of respondents or change of phone numbers d) increasing opportunity cost of participating in rounds as lockdown was lifted.[1]

Background characteristics of panel respondents at baseline

From the sample of respondents who appeared in all 6 waves, 5,180 respondents with no missing values were selected for the end-line report. This would allow for panel data analyses which are more efficient and robust than a time series analyses or a cross section analyses framework because they allow for estimates to incorporate variations (heterogeneity) across individuals at any point in time (between variation) and variation within individuals through waves (within variation). In other words, the panel data models use 5,180 times 6 or 31,080 data points. In this section we describe the background socio-economic characteristics of the sample and supplement the analysis with data from the household roster which was also collected at the baseline.

[1] The nominal incentive offered to participate per wave (NPR 200) declined in real value due to inflation observed during different waves of the survey.

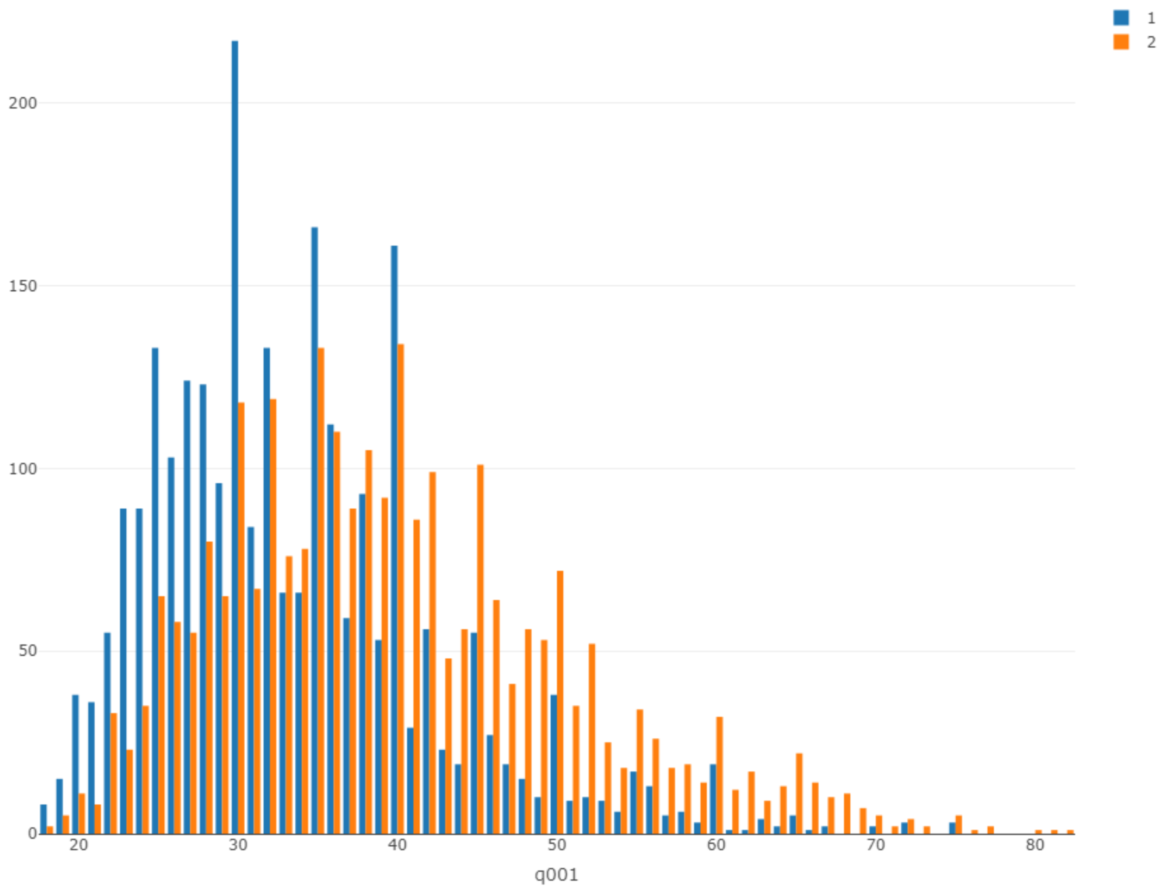


Figure 2: Age distribution of panel respondents (q001) by gender (1=Female, 2=Male)

49 per cent of the respondents were women, 51 per cent men. The average age of respondents was 37 years although there is a significant difference in the age distribution between males and females (Figure 2). The average age of male respondents was 40 versus 34 for female respondents.

The average household size was 5.54, at least one of whom was a child. From the household roster it is possible to surmise that in total, 28,676 family members were living with the selected 5,180 respondents who formed the panel data set. Of these family members, 10,942 were below the age of 17. Hence children comprise 38% of family members in respondent's households - 9 per cent were below the age of 5 (3 per cent below the age of 2 years) while a significant majority, 29 per cent, were between five and seventeen years of age. Those aged 60 or over, constituted about 8% of all household members. These ratios are similar to the overall population profile of Nepal as reported by Central Bureau of Statistics, Nepal (Central Bureau of Statistics, 2020).

Employment

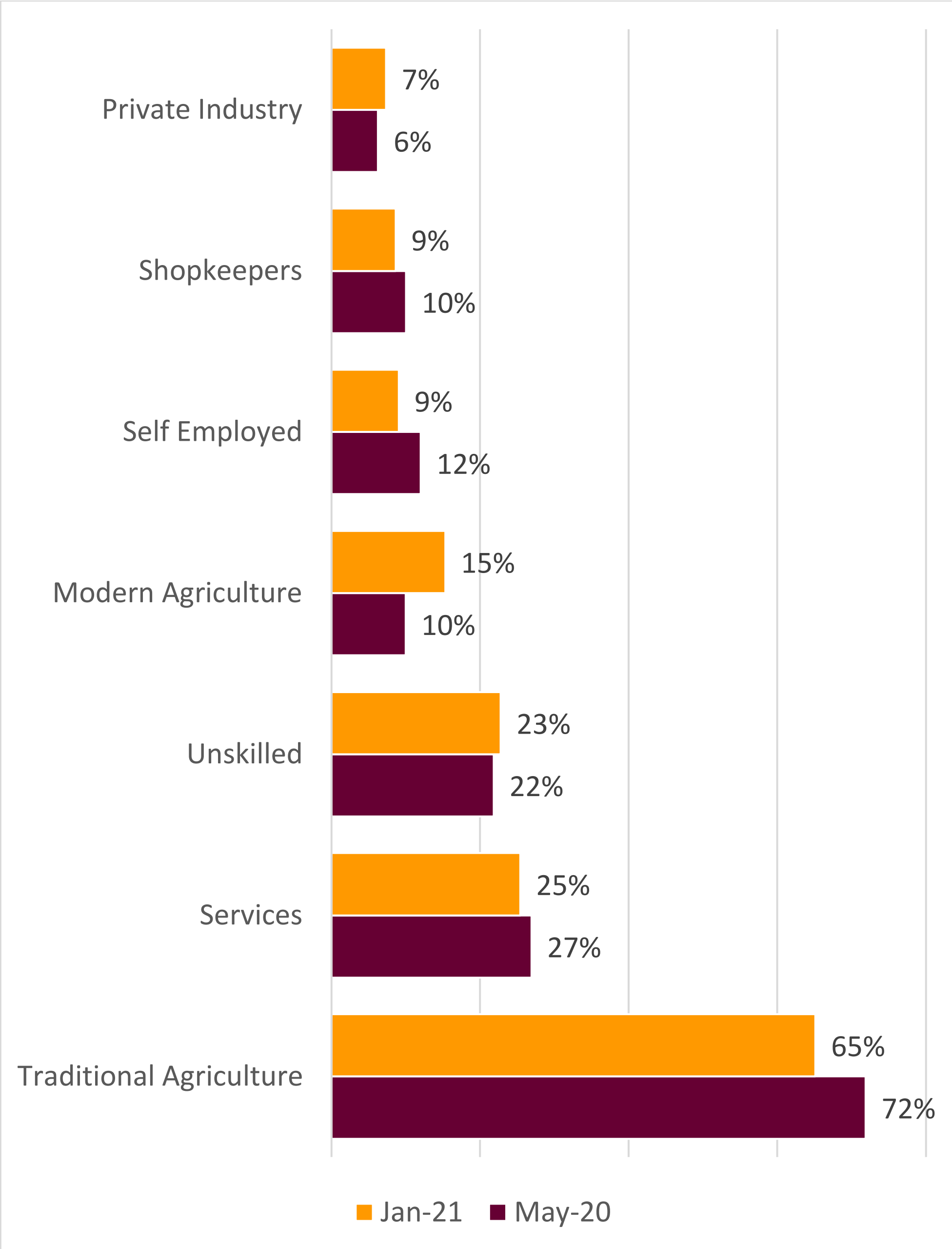


Figure 3: Sector of employment of family members in May 2020 and Jan 2021

The sector of employment of respondents and their families can be compared at the base line and end line (Figure 3). As corroborated by the Nepal Labour Force Survey 2017/18 (CBS, NPC, GoN, & ILO, 2020), the CFT data also confirms that agriculture remains the predominant sector of employment. However, its share has decreased in Jan 2021 compared to May 2020. Interestingly, comparing Jan 2021 with May 2020 employment patterns, modern agriculture, the private sector, and employment in daily wages saw increases while there was a decline in shop keepers, working in services, the self-employed and agriculture. Despite these changes, there has not been any significant shift in employment trends – rather these movements reflect differential recovery opportunities in different sectors.

Geographic distribution of respondents

The distribution of respondents by Province is shown in Figure 4. The distribution reveals over sampling in Lumbini, but otherwise a strong representation in all other provinces.

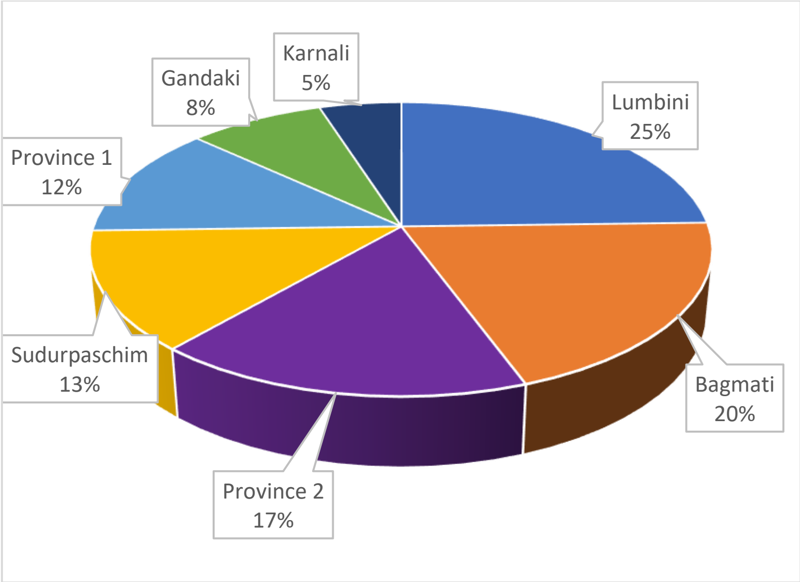


Figure 4: Distribution of respondents by Province

Type of residence

The sample covered more than 83% of Municipalities and was spread over 4 municipality types as defined by the government of Nepal (Figure 5). Respondents from urban municipalities comprised the majority of the sample followed by respondents in rural municipalities. About 13% of respondents came from metropolitan and sub-metropolitan municipalities.

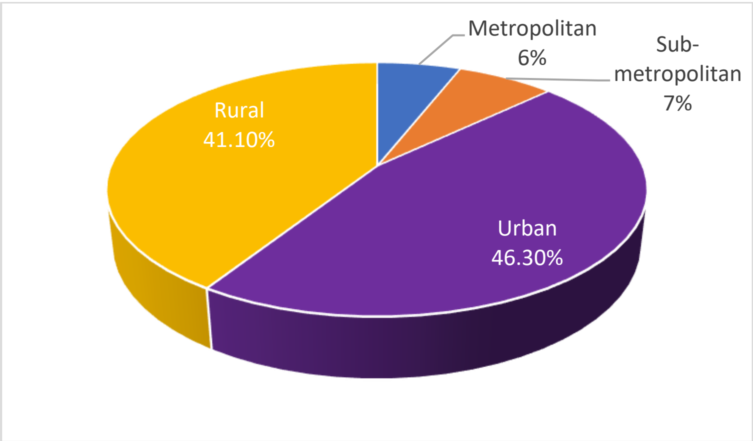


Figure 5: Distribution of respondents by type of municipality

Ethnicity

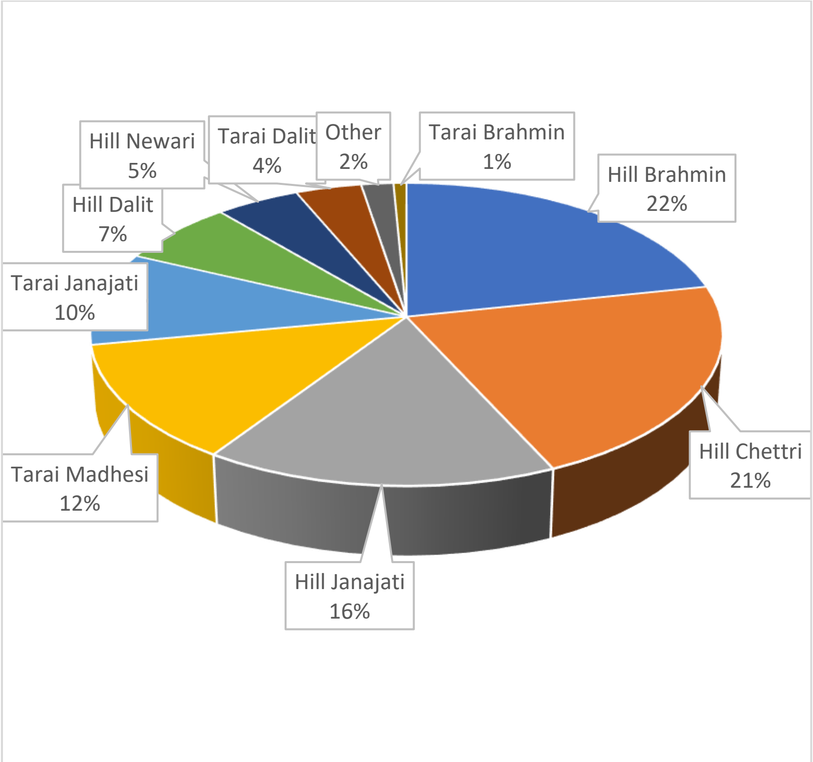


Figure 6: Ethnic composition of respondents

The distribution of ethnic groups in the sample (Figure 6) bears a strong correlation to the distribution of the sample across Provinces and within Nepal. The concentration of certain ethnic groups is stronger in certain Provinces. Janajatis comprised 26% of the sample: 16% Hill and 10% Tarai. Brahmins comprise 23% of the sample: Tarai (1%) and Hill (22%), Hill Chettris constituted another 21% of the sample. Tarai Madhesis made up 12% of the sample, while Dalits made up about 11% - 7% Hill and 4% Tarai. About 5% of the sample were Hill Newaris.

Disability status

14 per cent of respondents reported at least one family member with a functional limitation living with them. The average size of such households is 6.4, which is one more than the sample average while the average age for these households is also 1 year more than the sample average. In other words, households having a person with disability residing in the are a little older and larger. Respondents also reported that while 84 per cent of those with some or any functional limitations are above the age of 18, about 16 per cent were below the age of 18. Hence a little less than 1 in 5 of those with functional limitations are expected to be children.

There is considerable geographic variation between the provinces in reported disability status (Figure 7). Respondents from Karnali, Province 2 and Bagmati Provinces were more likely than respondents from other provinces to report that person with some or any functional limitation is residing with them. These provincial trends are similar to that obtained in the Nepal Multiple Cluster Indicator Survey, 2019 (GoN, NPC, CBS, & UNICEF, 2020).

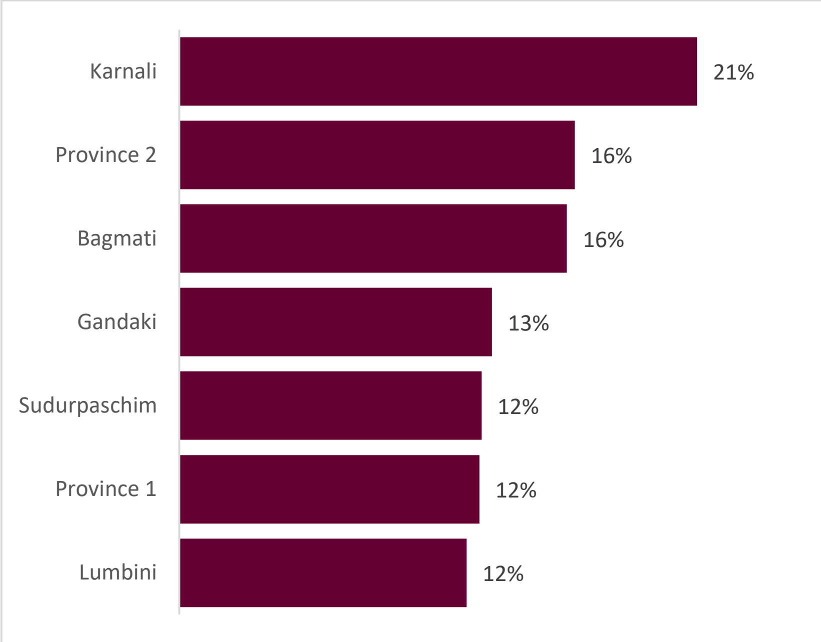


Figure 7: Per cent of respondents having a person with any disability living with them.

Gender of head of household

Approximately 22 per cent of the respondents came from female headed households. A female headed household can result from multiple social and demographic evens (e.g., death, migration). From the household roster, it is possible to deduce that female headed households had a disproportionately larger share of children living with them. Overall, children constituted about 38 per cent of total household members of respondents, but in female headed households, children comprised nearly 43 per cent of the total. In comparison, in male headed households, children comprised 37 per cent of the total household members.

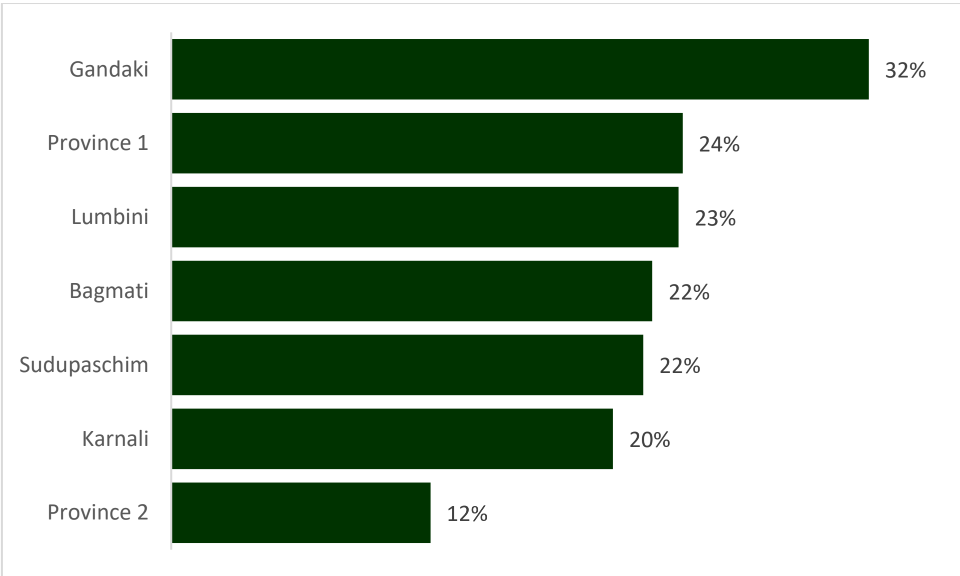


Figure 8: Distribution of female headed households.

The distribution of female headed households varies considerably in Nepal (Figure 8). Respondents from Gandaki, Province 1 and Lumbini were more likely to be living in female headed households compared to the four other provinces. Respondents from Province 2 were significantly less likely to report living in female headed households.

Key outcomes over time

The panel data structure allows us to analyse the following key variables that were captured across all six waves of the survey:

- Jobs or livelihood losses through waves
- Earning less than NPR 10K per month and reported income distribution through waves
- Declaring food as a top 3 immediate need
- Reduced dietary intake for children through waves
- Any violence witnessed through waves
- Children not studying through waves
- Coping strategies through waves

The advantages of panel data are numerous – they can control for variations within individuals at any point in time as well as variations of an individual's outcomes across time. In this section the time trends are analysed (Table 2). It is important to note that the base line (wave 0) took place while lockdown had been in effect for a few months – so people had time to 'adjust'. Waves 3, 4 and 5 took place after lockdown was lifted.

Table 2: Overview of select outcomes through all waves of the CFT

Wave/Round	% reporting jobs or livelihood losses	% earning less than NPR 10K per month	% reporting food as top 3 immediate need	% reporting reduced dietary intake for children	% reporting witnessing violence against woman and/or children	% reporting children not studying
0 (May)	55	11	28	25	5	41
1 (July)	61	44	21	21	8	17
2 (Aug)	53	66	35	25	6	21
3 (Oct)	46	63	30	25	6	6
4 (Dec)	33	46	20	18	7	6
5 (Jan)	19	40	18	12	6	3

In terms of losing jobs and livelihoods, the CFT data suggest a sharp worsening between May and July 2020 before improving. The percent of respondents reporting job or livelihood losses declined from 61% at its peak in July, to 19% in Jan 2021. The improvements are more visible after the lockdown was lifted as labour markets and economic activity began to improve compared to the lockdown period.

The data illustrate a continued shock in the income distribution all the way through Aug/Oct 2020 waves even as the jobs or livelihoods situation had improved. In other words, this situation suggests that overall earnings were low as people were either getting reduced salaries or none. In May 2020, around 11% of respondents reported earnings below NPR 10K per month. In July 2020, the number had increased four-fold to 44% and kept rising to 66% in Aug 2020 before declining only marginally to 63% in October 2020. Since then, there seems to be an improvement but even in the last round (Wave 5, Jan 2021), as many as 4 in 10 respondents reported household earnings to remain below 10K. Hence, it would be safe to conclude that many families and children living in them are still facing income insecurity – even as improvement is visible.

A significant share of respondents also reported requiring food as an immediate top 3 need in their families. The per cent of respondents declaring food as a top 3 need hit a maximum of 35% in August 2020 rising significantly from 28% in May 2020. From October 2020, as the lockdown was already lifted, supply chains and traders had begun to recover, the employment situation had begun to improve while incomes were showing signs of recovery. These positive factors also translated into a reduction in the per cent of families declaring food as their top 3 immediate need although even in the last wave (Jan 2021), nearly 1 in 5 respondents listed food as a top 3 immediate requirement. It is interesting to note that similar findings are reported in recent World Food Programme risk and vulnerability update for Nepal (WFP, 2020).

As families struggled with jobs and income losses, children's dietary intake was also adversely affected during the period under observation. Many factors including seasonal effects, incomes, and employment situation of the household, are responsible for children's dietary intake. Between May 2020 and October 2020, between 21-25% respondents reported reduced dietary intake for their children. Whether a coping strategy against increased income and employment uncertainty, or due to seasonal factors, the situation only improved in Dec 2020 and Jan 2021 when 18% and 12% respondents reported reduced dietary intake for children. Hence reductions in children's dietary intake were less severe after employment and income situation of households started improving. Despite the recent improvement, it is important to note that nearly 1 in 8 respondents had reported reducing their children's dietary intake as per data from Jan 2021 wave.

The CFT also queried respondents on witnessing violence against women and children. This variable is likely to be under reported for a variety of reasons. Nonetheless, through all the waves between 5-6% respondents reported witnessing violence against women and children. This number is quite high: 1 in 20 households reported witnessing violence in their neighbourhoods. Interestingly, witnessing violence remained more or less constant even as lockdown lifted and both employment and incomes began showing some recovery. These findings are consistent with data from helplines and police reports during this period which suggest an increase in violence and other protection related issues.[2]Since the NMICS 2019/20 (*ibid.)* also identifies significant child protection issues related to violence, this is a matter of great concern.

Children suffered a serious education setback as lockdown and school closures implied a cessation of normal schooling. In May, well in to the lockdown, around 41% respondents reported their children were not studying at all. Students who were studying were taking advantage of home learning or distance learning facilities not available widely and accessible for the poor or those living in remote areas. The per cent of respondents who reported children not studying at all declined through the waves as schools offered distance learning, reopened and lockdown was lifted.

The data suggest that some of these outcomes are more correlated to each other than others (Table 3). The strongest correlation is seen between the probability of job/livelihood losses and reduced intake of children's diets (+0.51). The probability of job/livelihood losses is negatively correlated to HH incomes. On the other hand, reducing dietary intake for children is positively correlated to job/livelihood losses (Campbell, 2021). Witnessing violence is also positively correlated with job or

[2] See also (Brooks, 2020) for global evidence

livelihood losses as is the probability of reporting children were not studying. These correlations are based on aggregated data over all the waves and presents an overall summary of how key outcomes influence each other. Household incomes are seen to be negatively correlated to job or livelihood losses, reduced dietary intake for children and to a lesser extent with witnessing violence. On the other hand, there seems to be a small positive correlation between incomes and children not studying. This can be explained due to various factors including the differential between schools opening and jobs and incomes improving. It is also noteworthy to see the positive correlation shown between households listing food as a top 3 need and the reduction in children's dietary intake.

Table 3: Correlations between select outcomes

Partial Correlation Coefficients (Pearsons)	Probability of job/livelihood losses	HH incomes	Food as top 3 need	Reduced dietary intake for children	Witnessing violence	Children not studying
Probability of job/livelihood losses	+1.00	-0.31	+0.43	+0.51	+0.14	+0.39
HH incomes	-0.31	+1.00	-0.43	-0.30	-0.03	+0.12
Food as top 3 need	+0.43	-0.43	+1.00	+0.48	+0.15	+0.26
Reduced dietary intake for children	+0.51	-0.30	+0.48	+1.00	+0.15	+0.21
Witnessing violence	+0.14	-0.03	+0.15	+0.15	+1.00	-0.04
Children not studying	+0.39	+0.12	+0.26	+0.20	-0.04	+1.00

From an equity perspective, the data suggest that recovery has been uneven and skewed in some instances towards the top quintiles. For instance, we can analyse the distributions of incomes as a box plot in each wave as shown in Figure 9 and observe that indeed after lockdown, the median income distributions (dash inside the box) started improving, particularly in Waves 4 and 5 which were held in Dec 2020 and Jan 2021 respectively. Nevertheless, the income distribution remains lower than what was observed in May 2020 (Wave 0). It is also clear that the top end of the boxes (higher quintiles) had a less severe shock and recovered quicker than those at the bottom end of the boxes (lower quintiles). A similar situation can be observed for all other variables when examining movements in the distribution across the waves (Figure 10 to Figure 14). This implies that there are strong disparities emerging with respect to background characteristics such as geography, ethnicity, being disabled, female headed households and others which translate to differential outcomes. These will be examined in detail subsequently through a panel data regression framework that will attempt to tease out the significant variables that cause variations across time as well as within individuals. Concerns about recovery within the context of Nepal and its economy have also been echoed in recent research (Keshav & Amit, 2020)

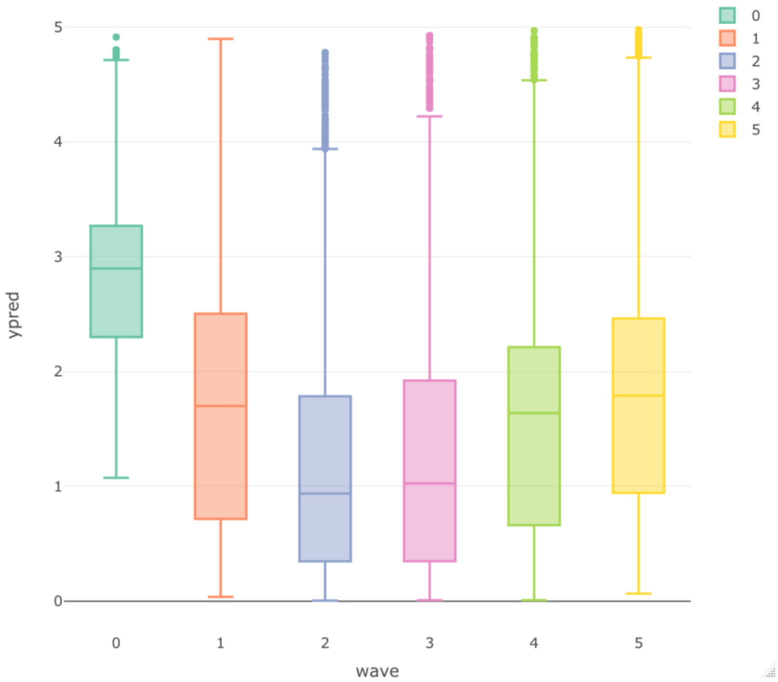


Figure 9: Income distribution (ypred) through all waves

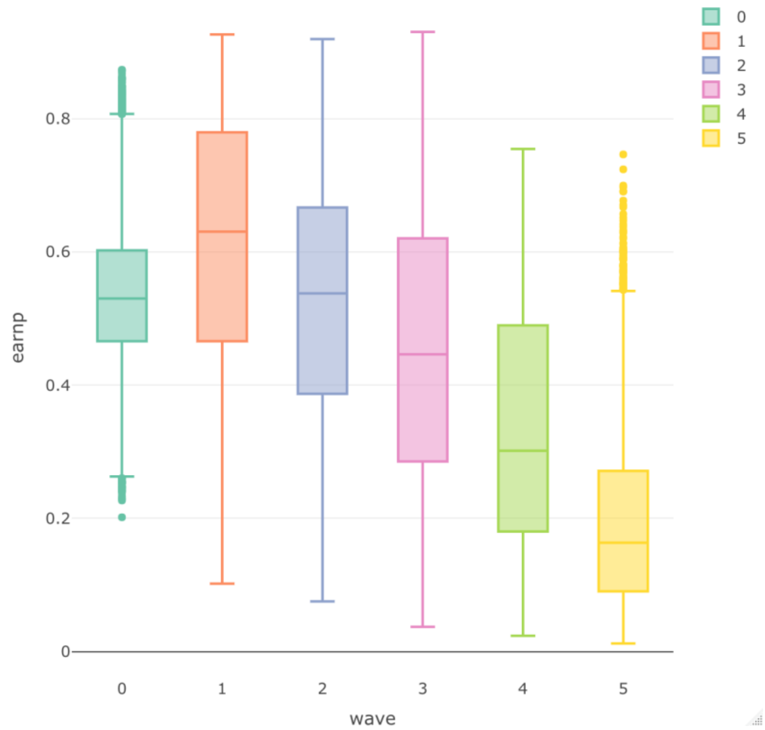


Figure 10: Probability of job losses (earnp) through all waves

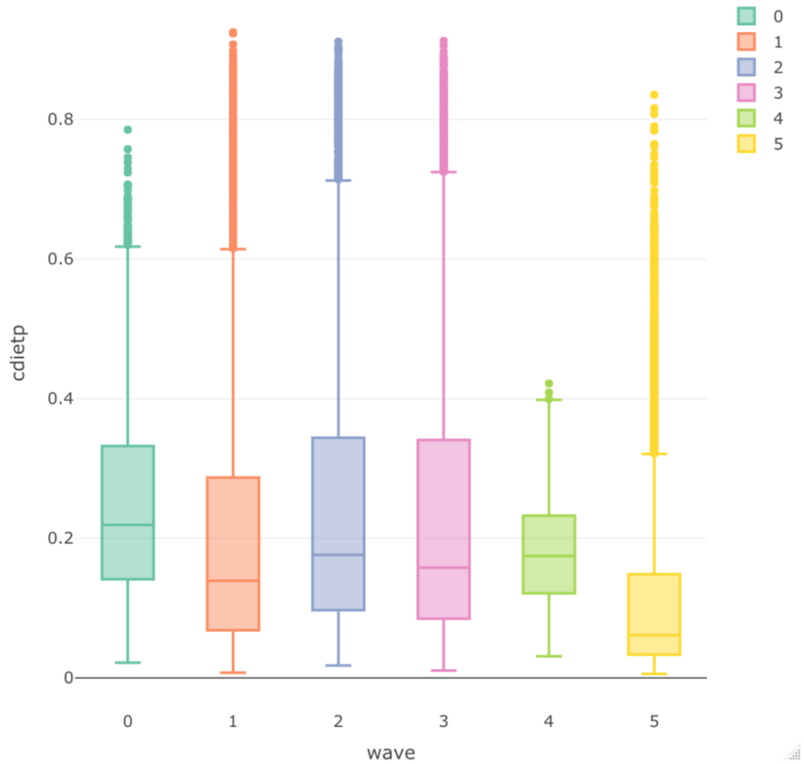


Figure 11: Probability of reducing children's diet (cdietp) through all waves

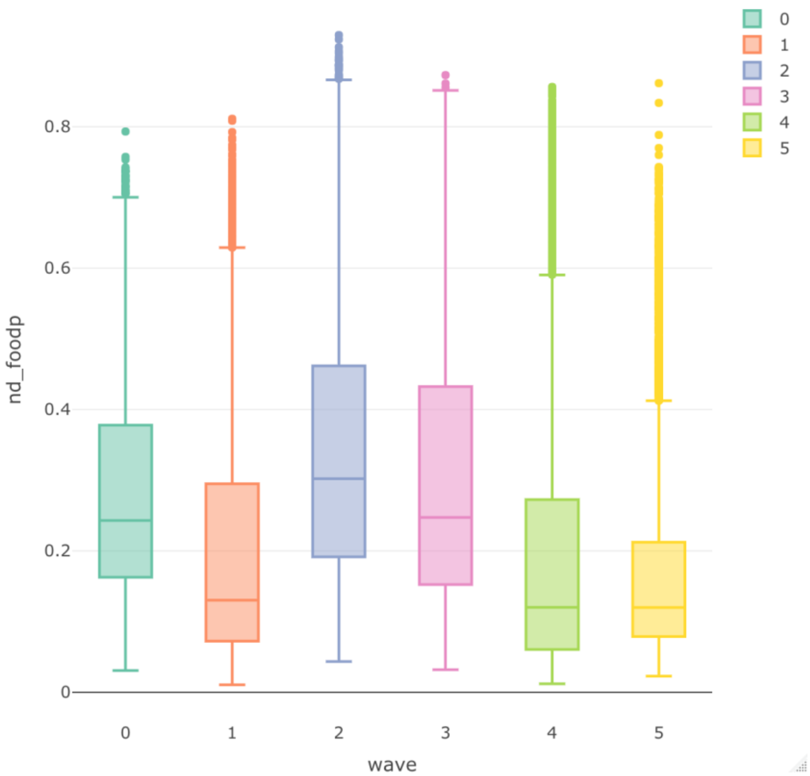


Figure 12: Probability of declaring food as an immediate need (nd_foodp) through all rounds

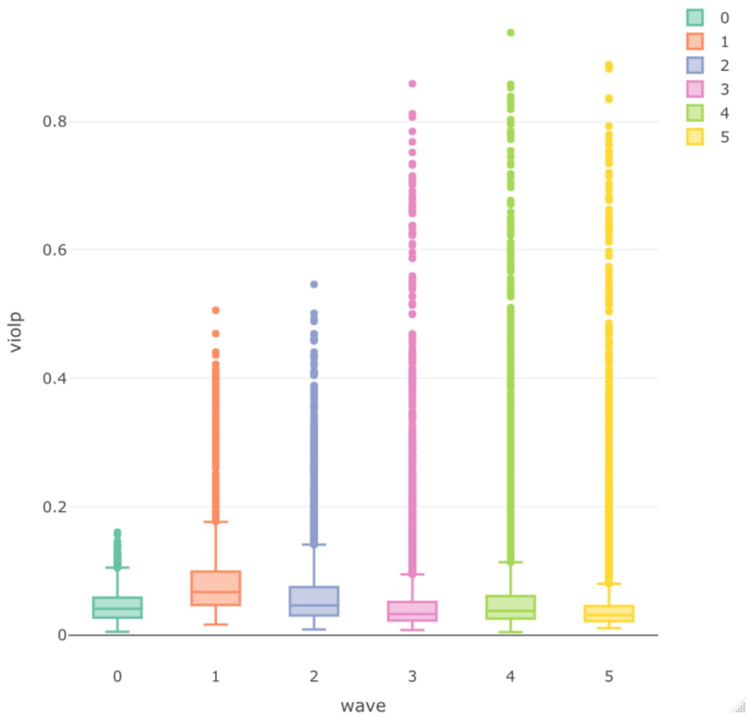


Figure 13: Probability of witnessing violence against women and children (violp) through all waves

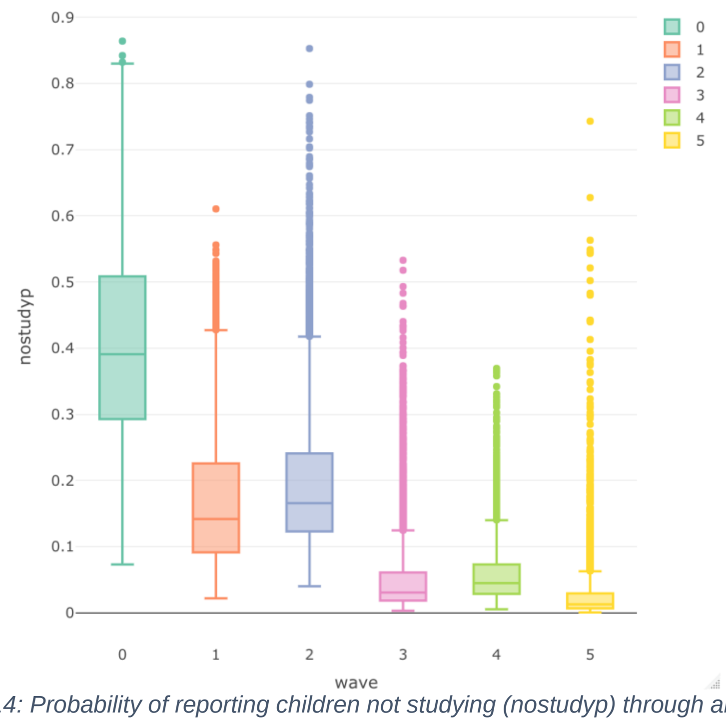


Figure 14: Probability of reporting children not studying (nostudyp) through all waves

Number of shocks

The panel data framework also allows tracking the number of times respondents reported shocks of various kinds. The resulting data are ‘count data’[3] and serve to highlight the frequency of shocks (incidence rate). The results are summarized in Table 10 below – the numbers in parenthesis denote percentages.

Table 4: Frequency of shocks

Frequency of shocks	Jobs loss	Income <10K	Reducing dietary intake for children	Struggling for food daily	Declaring food as an immediate need	Witnessing violence against women and children
0	513 (10%)	820 (16%)	2029 (39%)	3401(66%)	1790 (35%)	3963 (77%)
1	821 (16%)	683 (13%)	1386 (27%)	984 (19%)	1233 (24%)	788 (15%)
2	1117 (22%)	844 (16%)	774 (15%)	504 (10%)	898 (17%)	249 (5%)
3	1066 (21%)	934 (18%)	511 (10%)	212 (4%)	619 (12%)	107 (2%)
4	950 (18%)	913 (18%)	332 (6%)	79 (2%)	352 (7%)	47 (1%)
5	523 (10%)	769 (15%)	143 (3%)	--	191 (4%)	20 (<1%)
6	190 (4%)	217 (4%)	5 (<1%)	--	97 (2%)	6 (<1%)
N=5180. Due to rounding error the per cent totals may not be exactly 100%						

The findings suggest that a significant proportion of respondents reported numerous shocks over the 6 waves/rounds. In particular:

- 10% reported no job/livelihood losses over all rounds. 90% reported job losses more than 1 time. 63% reported job losses 2, 3 or 4 times. 14% reported job losses 5 or 6 times.
- 16% reported not having income less than NPR 10K/month over all rounds. 84% reported monthly household incomes less than NPR 10K more than once. 67% reported monthly incomes less than 10K 2, 3, 4 or 5 times. 4% reported monthly household incomes below 10K across all the rounds (6 times). 19% reported monthly income less than NPR 10K 5 or 6 times.
- 39% reported not having to reduce children’s diet in any of the rounds. 61% reported having to reduce their children’s diet at least one time. 52% reported having to reduce children’s diet 2, 3 or 4 times.
- 66% reported not having to struggle for food in any of the rounds while 34% reported having to struggle for food in at least 1 round. This question was asked only for 4 rounds/waves and hence the maximum value is 4. 2% of households reported struggling for food 4 times.
- 35% reported not needing food immediately. 65% reported food as an immediate top three need at least in 1 round. 53% reported an immediate need for food 1, 2 or 3 times.
- 77% reported not witnessing any violence against women and children. 23% reported witnessing violence against women and children at least once.

These reported frequencies are correlated to each other as well as to other background characteristics of the respondent and their households. These are discussed in detail in the technical annex.

[3] Count data are most often assumed to be generated by a Poisson process in statistics hence the use of a Poisson generalized linear model for the analysis. This model assumes that observed counts are generated by a Poisson process which is affected by covariates chosen for the analyses.

Coping strategies

Coping strategies also varied widely through the waves as households respondent to changing socio-economic risks. The main coping strategies utilized included incurring debt, reducing expenditures, depleting savings, borrowing from friends/relatives and depleting assets. For analytical purposes we also include reduction of children's diet as a coping strategy (Table 5).

Table 5: Coping strategies through time

Wave/Round	% reporting incurring debt	% reporting reducing expenditure	% reporting reducing savings	% reporting selling assets	% reporting relying on friends/relatives	% reporting reduced dietary intake for children
0 (May)	42	59	16	3	18	25
1 (July)	43	21	57	4	16	21
2 (Aug)	49	25	46	5	14	21
3 (Oct)	49	23	40	7	16	25
4 (Dec)	36	20	38	10	10	18
5 (Jan)	32	15	35	12	10	12

Interesting changes in coping strategies can be observed through the waves. While reducing expenditures were the dominant form of coping in May 202 (59%), in the other rounds respondents resorted more to increasing debt and depleting savings. By August 2020 nearly half the respondents reported having to resort to debt while a similar per cent reported depleting savings. These coping strategies could be linked to the fact that till August 2020 lockdown was in effect and respondents were facing income and employment shocks. As of Jan 2021, 32 per cent of respondents reported incurring debt to cope financially, down from 42 per cent in May 2020. Thirty-five per cent respondents reported reducing savings as a coping strategy in Jan 2021, more than double the rates observed in May 2020. In addition, an increasing per cent of respondents reported selling assets from May 2020 to Jan 2021. These findings suggest that household asset and wealth bases have been adversely affected during this time. It is also important to note that friends and family have continued to play an important role during this period. It is also important to note that in all the rounds, reducing children's diets were within the top 4 coping strategies employed by households (see also Figure 15). These coping mechanisms have also been reported in other studies in different contexts – for example, the USA saw a large increase in household debt during the Covid-19 pandemic (Cooper, Weinstock, & Mullins, 2021).

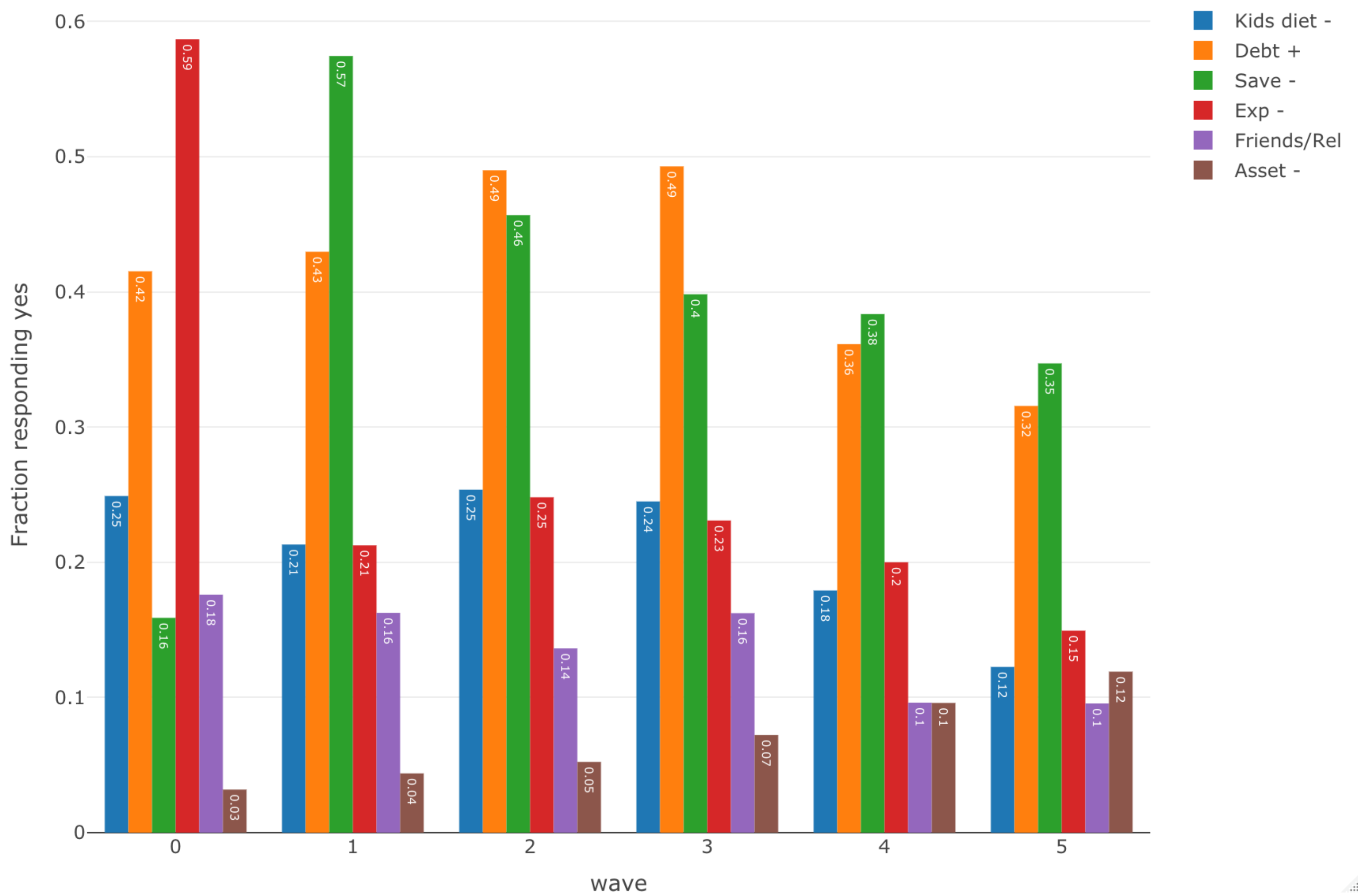


Figure 15: Coping strategies through time

Health

Respondents' health seeking preferences were heavily skewed in terms of health posts, followed by hospitals in the city (Figure 16). This behaviour is guided by many factors the most important of which are geography and income.

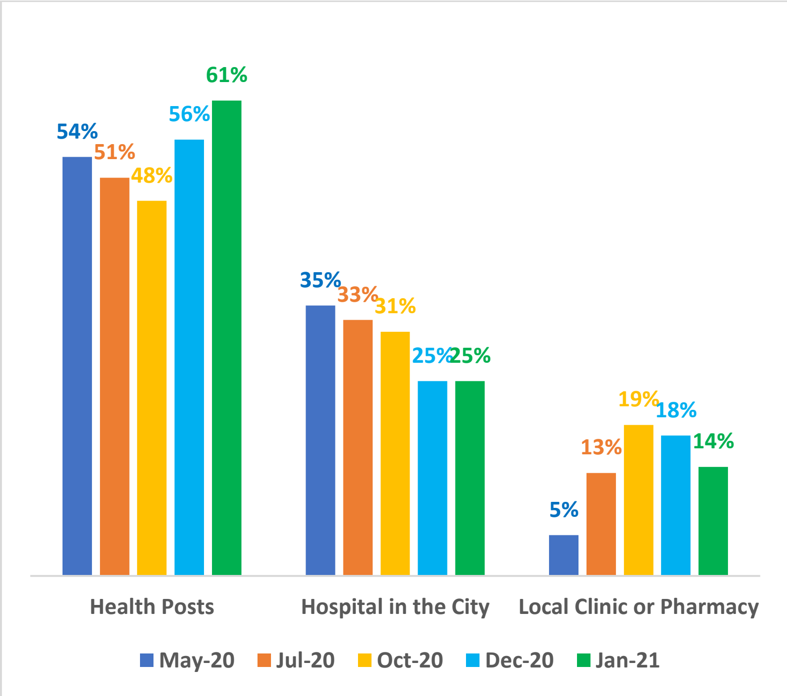


Figure 16: Health seeking preferences

Unpacking the January round data by background characteristics showed that nearly 1 in 10 respondents were preferring private health clinics because of quality and trust. The variation in health seeking preferences by background characteristics is shown in Figure 17.

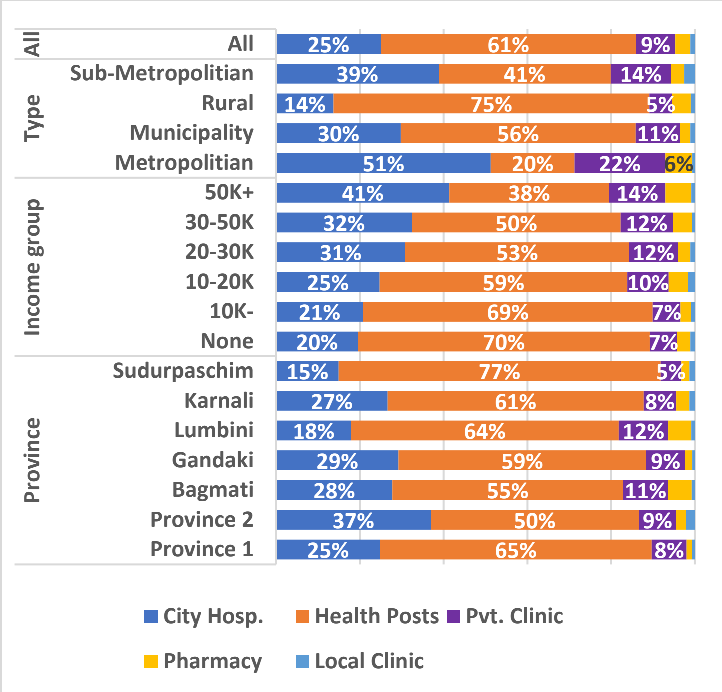


Figure 17: Variation in health seeking preferences by background characteristics (Jan 2021)

During the period under observation between 2-4% of respondents reported pregnancies in the household but respondents from Province 2, Karnali and Sudurpaschim consistently reported higher pregnancy rates. Reported ANC rates were also consistently high ranging between 95-98% in rounds where the question was asked. Health posts were the most preferred place for seeking ANC followed by city hospitals.

Nutrition

Aspects of nutrition related to children's dietary intake, the household struggling for food and declaring food as an immediate need are covered in great analytical detail in earlier sections. In this section, the focus is on breastfeeding and worrying about children becoming too thin. The latter is important given Nepal's failure to combat wasting over several decades.

Breastfeeding

The data suggest a decline in the percent breastfeeding the same (normal) over the 6 waves/rounds from 77-78% observed in the lockdown phase to about 70% in Jan 2021 (Figure 18). This was also accompanied by an increase in the percent breastfeeding less from 5% in May 2020 to 10% in Jan 2021. There is also an increase in the percent who had stopped breastfeeding from 0% in May to 6% in December before declining to 3% in Jan 2021. The most common reason cited for discontinuing breastfeeding was not enough breast milk. The data indicate that respondents from Lumbini, Karnali and Sudurpaschim were the least likely to be breastfeeding normally.

It is a matter of concern that despite global recommendations about the safety of breastfeeding in the context of Covid-19[4], 33-43% reported not feeling confident about breastfeeding children if mothers were suspected or diagnosed as having Covid-19. Respondents from Province 2 and those living in metropolitan areas were the most likely to not feel confident.

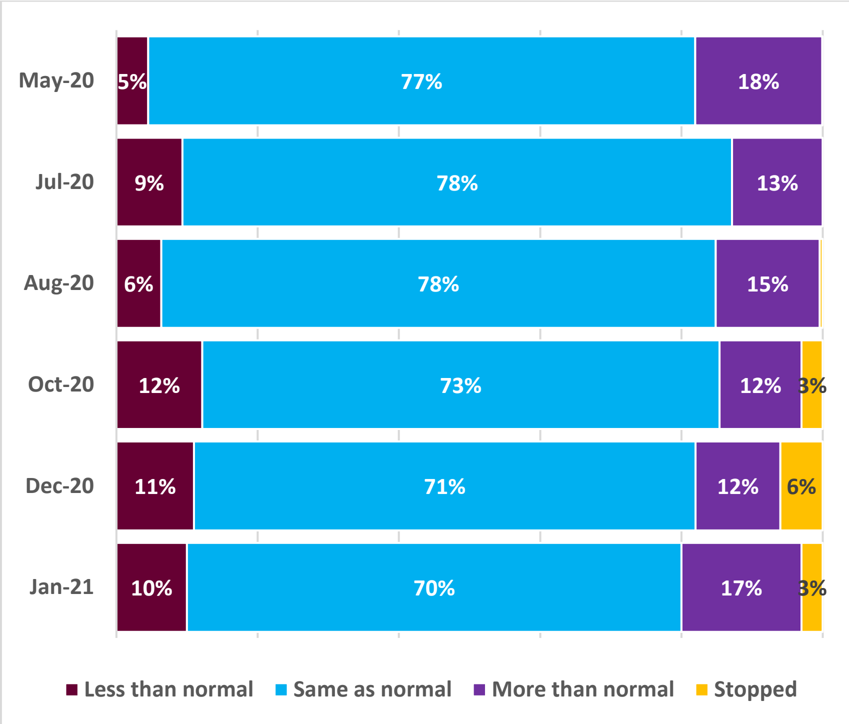


Figure 18: Breastfeeding frequency through all 6 waves

Worrying about children becoming too thin

Respondents also worried that their children were becoming too thin: between 9-17% respondents reported such worries over various waves/rounds of the survey (Table 6).

Table 6: Worrying about children becoming too thin

Wave/Round	Per cent worrying children becoming too thin
3 (Aug 2020)	17%
4 (Oct 2020)	13%
5 (Dec 2020)	9%
6 (Jan 2021)	12%
Note this question was only asked from round 3 onwards	

[4] Breastfeeding safely during the COVID-19 pandemic | UNICEF

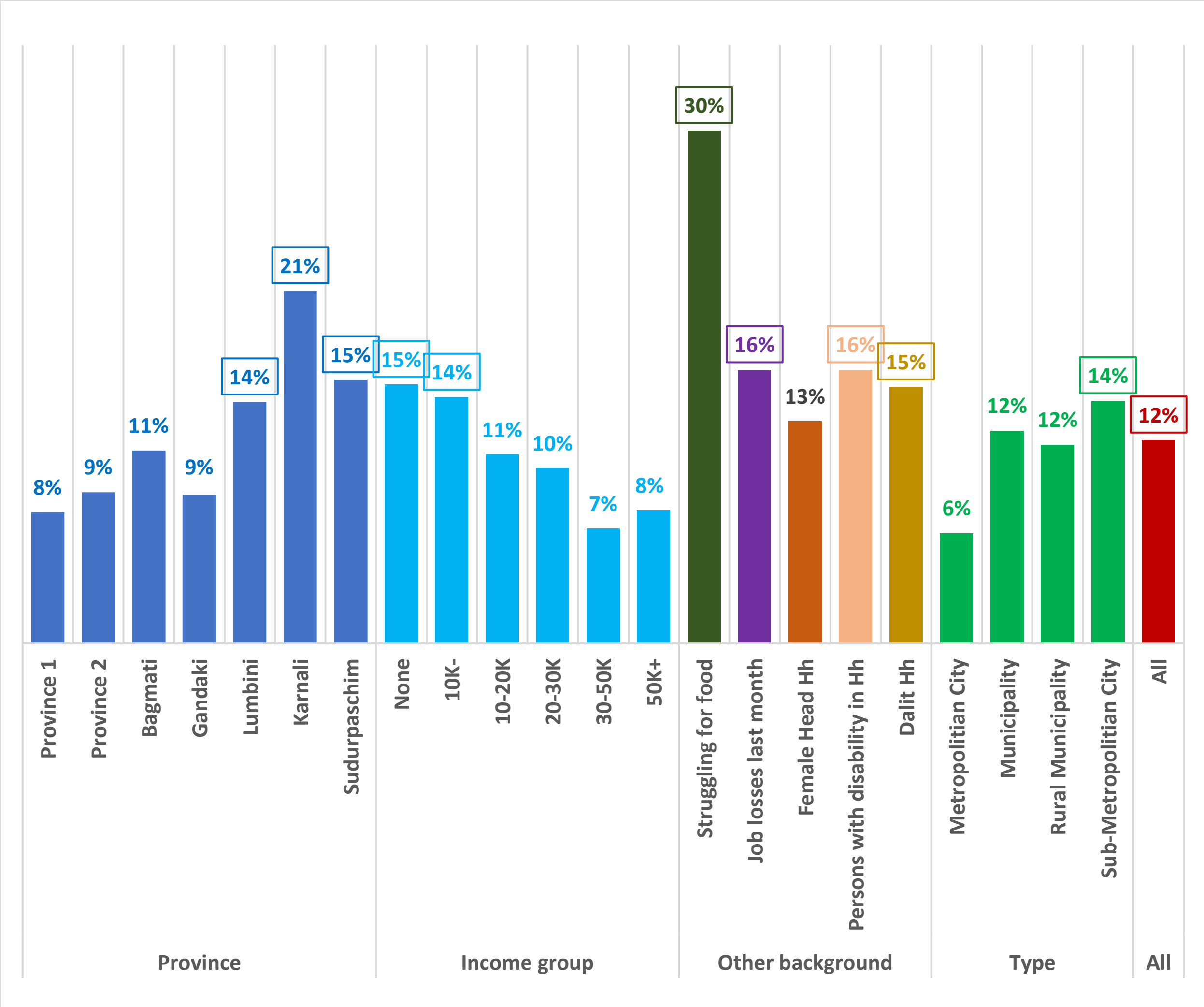


Figure 19: Worrying about children becoming too thin by background characteristics (Jan 2021)

In Jan 2021, respondents from Karnali and those struggling for food were the most likely to report worrying about their children becoming too thin (Figure 19). In addition, respondents from lower income groups, respondents reporting job losses, respondents having a person with disability living with them, Dalit households and respondents from sub-metropolitan areas were more likely to worry about their children becoming too thin (compared to the average)

Public Health and Safety Measures (PHSM)

Significant changes in behaviour were observed when examining the data on safety measures deployed by residents and their families when comparing May 2020 and Jan 2021(Figure 20). During the baseline (May 2020) the lockdown was in effect.

The most common safety measures were washing hands frequently with soap (90%), staying home (82%) and wearing masks when outside (78%). However, by Jan 2021, when lockdown was lifted, only 18% reported staying at home. The use of hand sanitizers as well as wearing masks went up, but all other safety measures were reduced. Staying away from people (maintaining social distancing) was reduced significantly from 58% during the lockdown to 40%. There was also a reduction observed in handwashing behaviour from 90% to 85%.

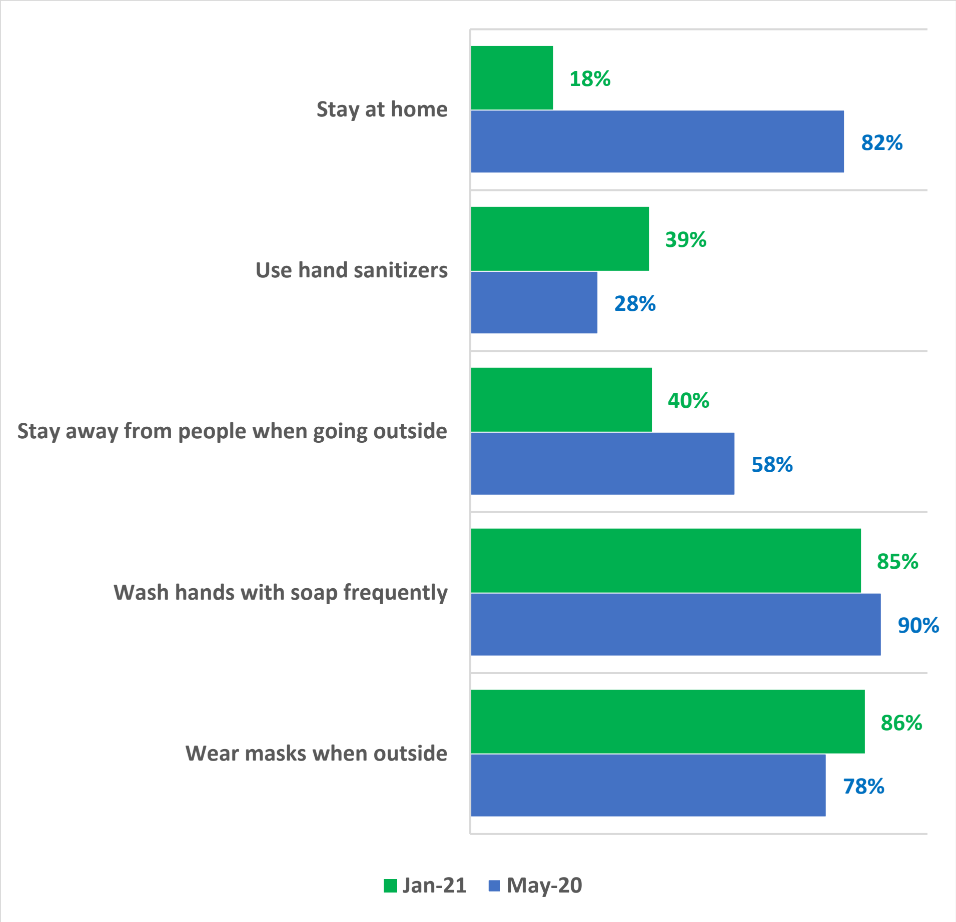


Figure 20: Safety measures reported by respondents (May 2020 and Jan 2021)

These results vary greatly by background characteristics such as geography, income levels, population density and other characteristics including the perception of risks. The variation by Province across the two rounds is shown in Figure 21. The figure plots safety measures households were adopting in terms of distancing, staying at home, wearing masks, using hand sanitizers and washing hands in May 2020 and Jan 2021 (prefixed by 0 and 1 in the graphs)

In May 2020, residents from Gandaki and Lumbini were the most likely to practise social distancing while residents from Bagmati were the least likely. Residents from

Karnali were the least likely to stay at home during the lockdown. Residents from Province 2 were the most likely to wear a mask, residents from Bagmati were most likely to use sanitizers. Province 1 respondents were least likely to wash hands with soap frequently.

In Jan 2021, lockdown had been lifted for a few months. Unlike in May 202, respondents from Province 2 were the least likely to practise social distancing. As noted earlier, there was a significant decrease in the share of respondents staying at home. Respondents from Province 2 were the least likely to stay at home, wear masks and wash hands frequently with soap. As noted earlier, there was an increase in the use of hand sanitizers.

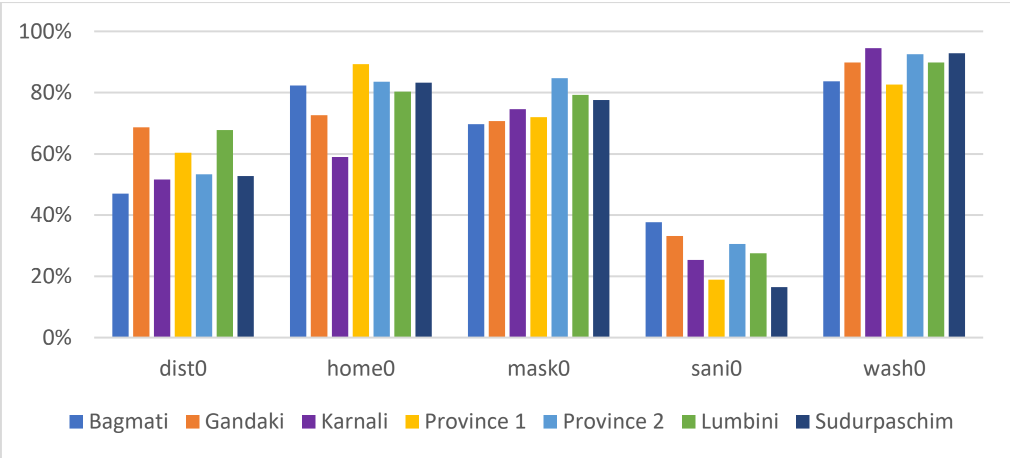
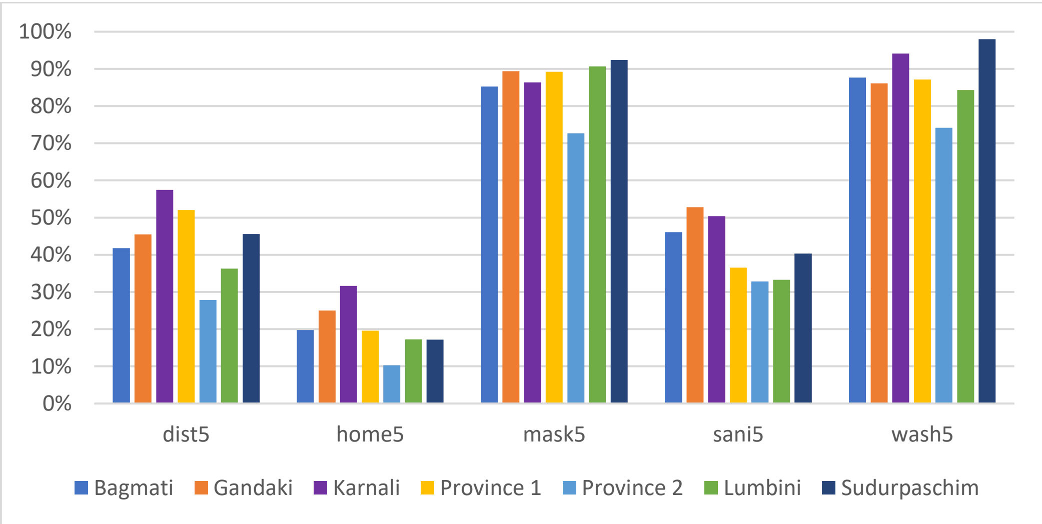


Figure 21: Variation in safety measures by Province in May 2020 (above) & Jan 2021 (below)



Children working for income

The CFT captured information on children working for four of the six waves – Wave 0 (May 2020), Wave 1 (July 2020), Wave 2 (Aug 2020) and Wave 3 (Oct 2020).[5] The information was obtained directly from children's primary caregiver (i.e., the respondent) by querying whether children earned income during the previous month. The baseline survey also contained a question on whether children were working or earning income prior to the lockdown. The results highlight the multiple and overlapping challenges and deprivations that households with children have to endure. In this section, the causal correlates of household where children are working to earn income are examined in detail.

The percent of respondents who reported their children working in their homes declined strongly from over 30% pre-lockdown to 8% during May 2020 and then fell further to 1-2% thereafter. This trend can be explained by a variety of reasons – the most important being the collapse of labour markets during the first wave of the Covid-19 pandemic in Nepal and physical restrictions on movement. Furthermore, at this time both adult and child labour networks and pathways to work were severely affected. Secondly, there was the seasonal impact – where the harvest season (which absorbs a lot of children working) was over in the rounds following the baseline. This 'beneficial aspect' of Covid-19 in so far that it reduced children working for income needs to be unpacked further as further analysis suggests that the probability of children working for income also depends on a range of factors. Furthermore, the analysis fails to capture children working without pay.

The most important determinant of children working for incomes in Wave 1-Wave3 appeared to be whether the household reported children working prior to the baseline. A standard binomial regression framework (Logit model)[6] as well as more recent Random Forest Decision Making Algorithms[7] are used to derive the predicted probability of a respondent reporting that their children would be working at home as well as the 'important' variables correlated with this answer. The binomial regression framework uses a Logit model to convert a binary 0,1 response into a continuous probability based on explanatory variables. The Random Forest method approaches the data as a classification (or prediction) problem based on the features of the data (explanatory variables) but does not know anything about the functional dependence between them – this is derived through decision trees. Instead of regression coefficients – the 'importance' of features deemed significant by the model in predicting outcomes are reported. Both these techniques are useful for decision making in different settings.

The following models were evaluated using the sample of respondents who appeared in all 4 rounds for which child labour data are available. First, a base model where the outcome variable (respondent reporting that their children were working for income) is assumed to depend on monthly household income is used to evaluate the strength of

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[5] After October 2020, the question was dropped and replaced with whether the respondent had observed children's economic exploitation in the neighbourhood.

[6] [How to: Binomial regression models in R | R-bloggers]

[7] [Random Forests Algorithm explained with a real-life example and some Python code | by Carolina Bento | Towards Data Science]

the relationship. The next model corrects for unobserved heterogeneity due to provinces using a fixed effect formulation – where a separate relationship between children working and household income is derived for each province. Finally, the model is expanded to include other background variables such as disability status of the household, whether the household also reported changing children's diets and so on. The last model was evaluated using two techniques. The first was the well-known binomial regression frameworks where Logit regressions were used. The final model was also evaluated using a Random Forest Classification Algorithm where the most important 'features' – the explanatory variable – are derived using a decision tree with over 100,000 nodes consisting of different combinations of explanatory variables to arrive at the most important ones that contribute to the event being observed (i.e., respondent reported children are working). Although the Random Forest models produce more reliable estimates in classification regressions (because they don't require the data to be scaled), we report estimates from both as the latter also allows us to study the numeric impact of factors on the outcome.

The base model confirms that household income is a significant predictor of whether respondents report that their children are working to earn incomes or not. The regression result obtained suggests that the log of the odds ratio of reporting children working decreases significantly as predicted incomes rise. The post estimate fit shows a strong overlap between predicted probability of reporting children are working and predicted income levels.

As per the base model results, the (log of the) odds ratio of a respondent reporting their children are working, z(clab00) decreases by 0.12 when income increases by 1 unit. The result is significant at the 95% confidence interval and reveals a strong negative relationship between incomes and the probability of children working for income (Figure 22).

$$z(clab00) = -0.57 - 0.12\boldsymbol{ypred}$$

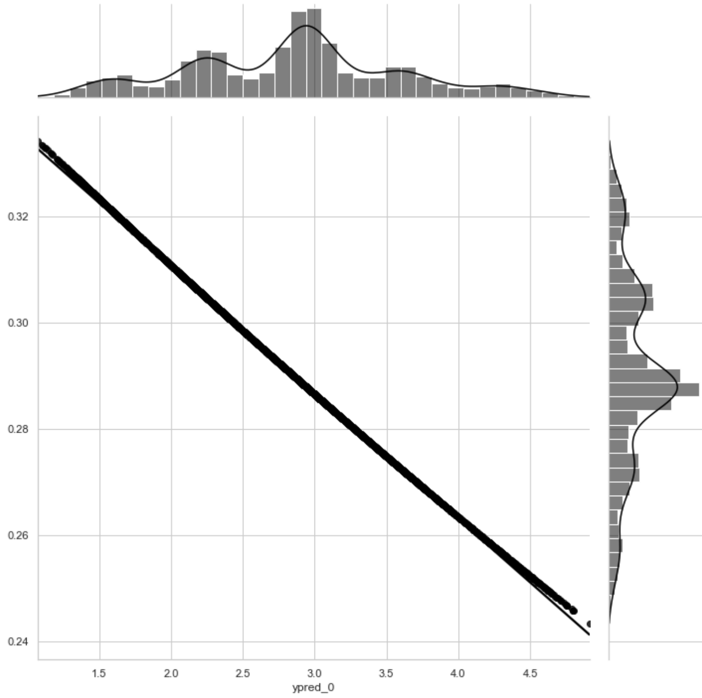

Figure 22: Predicted probability of reporting children working (y-axis) versus predicted incomes (ypred_0,scaled, x-axis)

However, this model tends to suffer from heterogeneity bias arising from ignored variables that also affect the outcome variable as there are many other variables that influence the decision apart from income. One such variable is geographic location. Adding in dummies for provinces improves the efficiency of the estimates considerably, and reduces the emphasis on income as there are now geographic fixed effects acting on the data. In particular, we assume in the fixed effects formulation that each geographic unit behaves the same but may differ in base levels observed. The 2nd model results are shown in the equation below with significant coefficients (95%+) shown in bold. Note that Province 1 is the counterfactual (1 province has to be dropped to avoid the collinearity trap):

$$\boldsymbol{z(clab00)} = \mathbf{-0.78 - 0.13}\,ypred_0 + \mathbf{0.42}\,Pro_{02} + \mathbf{0.23}\,Pro_{03} + 0.06\,\boldsymbol{Pro_{04}} + \mathbf{0.48}\,Pro_{05} + \mathbf{0.33}\,Pro_{06} - 0.06\,\boldsymbol{Pro_{07}}$$

The fixed effects results suggest that incomes still play a critical role in explaining the (log odds of the) odds ratio for children working for incomes prior to lockdown, z(clab00). The numeric sign in front of the coefficient indicates the direction of influence. The values indicate the influence on the (log of the) odds ratio. Gandaki and Sudurpaschim respondents had the smallest log odds of a respondent reporting their children are likely (with respect to the counter factual who are counterparts from Province 1). Respondents from Province 5 were most likely to report their children while respondents from Province 2, Bagmati, Lumbini & Karnali had a higher (log of the) odds ratio of reporting their children were working prior to lockdown. In other words, the impact of introducing fixed effects yields a parallel but different regression line for each Province – the slopes are the same but the intercepts will be different. The fixed effects formulation can be illustrated by plotting the predicted probability of a caregiver reporting their children working for income against their household level income for the past month (Figure 23). Note that the intercept is significant – it reflects exogenous variables not specified in the model such as cultural factors, seasonal patterns and so on.

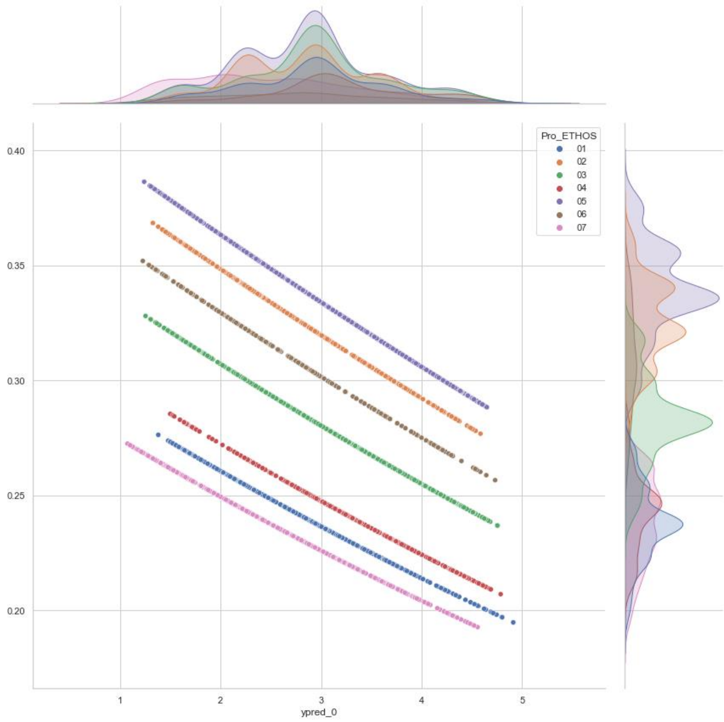

Figure 23: Province fixed effects: Predicted probability of reporting children working (y-axis) versus predicted incomes (ypred_0, x-axis)

In terms of model specification, there are still problems with omitted variables such as background characteristics of the respondent and household. The full model specification uses the following variables shown in Table 6:

Table 7: Variables used in the full model for children working for income

Variable Name	Description
Ypred_0 **Pro_ETHOS**	Income levels at baseline
Sratio	Ratio of number of children to family size
Q001	Age of respondent
Wrk_agr	Whether respondent working in trad. agriculture sector
Nd_food0	Whether respondent reported needing food as a top 3 immediate need in the baseline
Cdiet0	Whether respondent reported reducing children's dietary intake at baseline
Nostudy0	Whether respondents children were studying or not
Femhd	Whether household is female headed
Disab	Whether household has any disabled person living in the HH

The results of this multivariate binomial regression are interesting and highlight several overlapping deprivations along with respondents reporting their children having to work for income. Figure 24 plots the estimated coefficients along with their confidence intervals and medians. Their distance from zero indicates whether they are significantly different from zero (have no impact). When other variables are included, the significance of predicted income (ypred_0), although still showing a negative relationship, disappears as this effect is absorbed into other variables it is correlated with such as the need for food, or having to reduce children's diets. The number of children relative to household size is the most important predicter for a respondent reporting their children were working. Age (q001) is also an important predicter – older respondents probably had older children who were working. Households reporting an immediate need for food in the baseline (nd_food0) were significantly more likely to report that their children were working for income before lockdown. A similar strong effect is observed for households reporting having to reduce children's diet (cdiet0). In addition, female headed households (femhd), households where children were not studying (nostudy0) were more likely to report their children were working for income. Disabled households are also more likely to report their children working for income, but the impact is not so significant as other variables. In short, the probability of respondents reporting their children working for income, in addition to monthly household income, relies on a wide range of factors but is also highly correlated to other deprivations in nutrition and education.

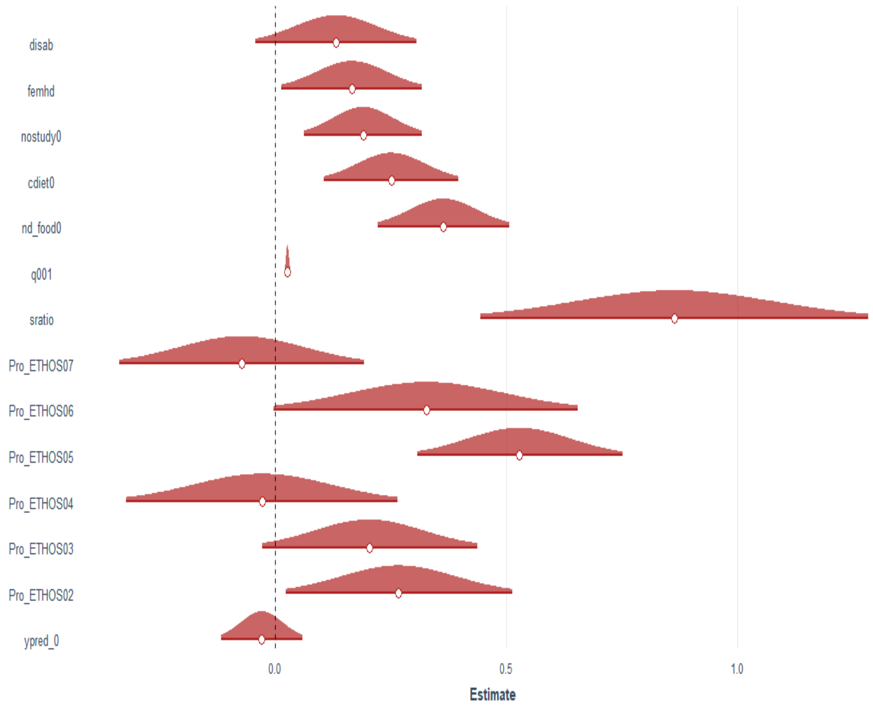

Figure 24: Coefficient plot - Children working for income

The random forest regression classification also suggested very similar results with baseline incomes as being selected as the most important feature in determining if children were likely to work for income or not.

Conclusion

The end line report made use of the panel data structure using all 6 waves/rounds for those respondents who appeared in all the rounds. This balanced panel data structure allowed a deep and thorough analysis of some key outcomes such as income levels, job losses, coping mechanisms including reducing children's dietary intakes, struggling for food, needing food, witnessing violence and children not studying. The causal correlates were identified and should be useful for designing context specific policies. Another important contribution of this end line report is the ability to analyse the frequency of shocks (select indicators only) and use a regression framework to identify variables that affected the frequency of shocks either positively or negatively. Finally, this end line report was able to show that although recovery was evident for key outcome variables, it has been highly uneven and inequitable.

This report concludes that the impact on children can be said to have been severe. Apart from school closures and discontinuities in the education cycle, many children were affected as their families suffered multiple and numerous shocks to incomes and jobs – globally proven to be among the two most important factors in relation to child welfare. Children's dietary intake was also found to have been reduced as households deployed coping mechanisms such as increasing indebtedness, reducing expenditures, drawing down savings and selling of household assets thereby reducing the wealth base. At the same time many children were living in households reporting having witnessed violence against women and children. Concerns related to trafficking, child elopement and child labour were also identified in some of the rounds – these were reported in the individual round CFT power point analyses (UNICEF & SCIN, 2020/2021).

Technical Annex: Panel data analysis

This section uses a panel data (also known as longitudinal data) approach to isolate some variables that could be affecting outcomes. Panel data models have received increasing attention over the last four decades due to the enormous information content and a wide variety of standardized models are available. Panel data implies that we have a set of observations on outcomes at different points in time for a cross section of people. Since we are using only those respondents who appeared in all waves, it is a balanced panel data where 5,180 individuals are followed over 6 waves.

We focus on 6 outcomes of interest identified earlier – so six models will be analysed. A regression framework assumes that these outcomes are linked to a set of common explanatory or background variables. The same set of explanatory variables are used for all 6 regression models. If we let i denote the individual/entity and t denote time, then a panel data set can be defined as a collection of data points denoted by $(X_{i,t}, Y_{i,t})$, for *i*=1…n and t=1…T. In this formulation X denotes background characteristics and Y denotes outcomes. In other words we postulate $Y_{it} = f(X_{it})$. There are several different approaches to specifying the exact functional formulation for *f* depending on the data structure.[8] Panel data are typically 'long' in the cross-section and 'short' in the time dimension. In our case we have 5180 observations observed across 6 waves, so n=5180 and T=6. In other words we have 31080 observations in all (nxT).

There are numerous advantages in using panel data. It allows us to control for observations we are unable to observe directly or measure like cultural factors or variables that change over time but not across individuals (e.g., everyone is affected by the lockdown that was first imposed in Feb 2020 and then lifted in August 2020). It can also accommodate variables that change over time like income levels. Thus it accounts for individual heterogeneity. In addition, it allows us to analyse the data at different hierarchical levels including at the individual level, district level or other geographic aggregated level (hierarchical models). Most importantly, individual

[8] (Yves Croissant, 2018)

observations over time may be correlated and this correlation can be captured through a dynamic specification of the model.

Our point of departure is the simplest assumption that our outcomes (*Y*) are generated by the following data generation process:

$$Y_{it} = EY_{it} + \varepsilon_{it}$$

Where ε_{it} is a idiosyncratic or random error term and represents the deviation from the mean denoted by EY_{it}. The *i* and *t* subscripts denote as before individuals and time. Depending on the specification of EY_{it} different models arise. The basic formulation is

$$EY_{it} = \alpha_{it} + \beta_{it}X_{it}$$

As stated above, the model is not estimable without making simplifying observations about the parameters of the model. A 'homogeneous' model specification sets $\alpha_{it} = \alpha$ and $\beta_{it} = \beta$ for all i and t. The resulting model is a 'pooled regression' model where we have

$$EY_{it} = \alpha + \beta X_{it}$$

This specification however, ignores individual heterogeneity and assumes that all individuals are homogeneous and the passage of time has no effect. To model individual heterogeneity the simplest approach is to specify $\alpha_{it} = \alpha_i$ for all t yielding:

$$EY_{it} = \alpha_i + \beta X_{it}$$

The specification is linear and assumes that the mean of Y_{it} denoted by EY_{it} is conditional on an 'intercept term' α and a 'slope term' β – collectively known as the coefficients of the specification. This is also known as the standard 'fixed' effects model (aka 'within' model) where individual specific variability is captured by α_i but the slopes or coefficients β are identical or homogeneous across individual entities. The coefficients in the fixed effect specification are unknown (but fixed) parameters to be estimated by the model. If we assume that the coefficients are random variables themselves instead of parameters, we have the 'random effects' models (aka 'between' model).

For both sets of models, the data consist of all those who participated in all 6 waves/rounds consisting of 5,180 respondents thereby yielding a balanced panel of 31,080 data points. In order to account for non-linearities and obtain more robust estimates log transforms were used for the analyses.

Fixed Effects Model (Within model)

For the fixed effects models, the description of the variables is as follows (Table 8):

Table 8: Description of variables used in fixed effects models

Variable name	Variable description	Mean value (actual variable) across all 6 waves/rounds

ld	Dummy variable for lockdown months	0.50
learnp	Log of predicted probability of job losses	0.44
lypred	Log of predicted income group	1.74
lcdiet	Log of predicted probability of reducing children's dietary intake	0.21
lnd_foodp	Log of predicted probability of household declaring food as an immediate need	0.25
lviolp	Log of predicted probability of witnessing violence against women and children	0.06
lnostudyp	Log of predicted probability of reporting children not studying	0.15
ldebtp	Log of predicted probability HH incurred debt	0.41
lexpp	Log of predicted probability HH reduced expenditures	0.27
lsavep	Log of predicted probability of HH reducing savings	0.39
lassetsp	Log of predicted probability of HH selling assets	0.07
lfriendsp	Log of predicted probability of HH relying on friends/relatives	0.14

Income distribution

The following panel data fixed effects (within model) regression equation was obtained for (log) predicted incomes.[9]

$$\begin{aligned} lypred = {} & 0.37\boldsymbol{ld} - 0.27\boldsymbol{learnp} - 0.05\boldsymbol{lcdietp} - 0.26\boldsymbol{lndfoodp} + 0.01lviolp \\ & - 0.37\boldsymbol{ldebtp} + 0.23\boldsymbol{lexpp} - 0.19\boldsymbol{lsavep} - 0.19\boldsymbol{lassetsp} \\ & - 0.10\boldsymbol{lfriendsp} \end{aligned}$$

The equation is easy to interpret and shows what happens to the expected value of (log) predicted incomes as the right-hand side variables are increased by one unit controlling for all other variables. The value of the coefficients indicates the relative strength of impact. A positive sign indicates movement in the same direction and a negative sign shows movements in opposite directions. These results show that (log) predicted incomes were higher during the early phase of lockdown as log of predicted income reduced by 0.37 as lockdown was imposed. Log of predicted incomes were also significantly lower as the (log) probability of jobs/livelihood losses went up, were lower as (log) probability of reducing children's diets went up, were lower as (log) probability of households declaring food as an immediate need rose, were higher as the (log) probability of households witnessing violence (but not significantly), were lower as the (log) probability of households resorting to debt went up, were higher when (log) probability of households reducing expenditure went up, were lower when (log) probability of reducing savings, selling household assets and relying on friends went up. These are also shown below in the coefficient plot (plots the coefficients of the equation) in Figure 25 below. Each of the estimates is plotted (with the distribution) and the distance from 0 – either positive or negative denotes the strength of the impact. Variables very close to zero may not be assumed to be significant. Variables

[9] There were obtained using the packages plmr from R

to the right (and further) from 0 indicate a positive impact on the outcome variable while coefficients entirely to the left of the zero line indicate negative impacts on the outcome.

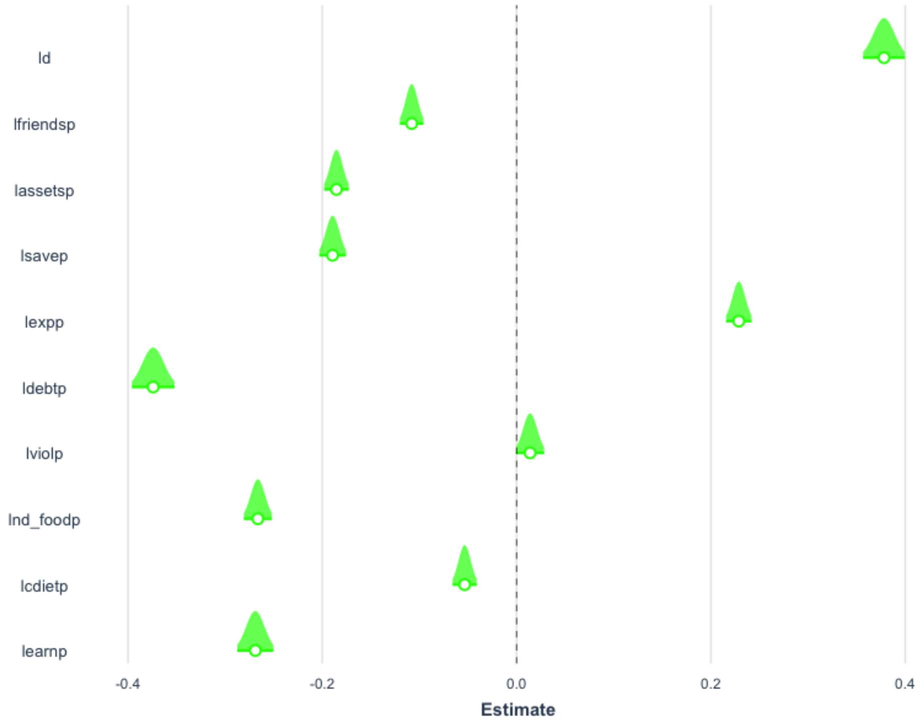

Figure 25:Within model (Fixed effects) coefficient plot of income distributions

Job losses

In terms of jobs/livelihood losses the following equation was obtained:

$$learnp = 0.37\boldsymbol{ld} - 0.11\boldsymbol{lypred} + 0.08l\boldsymbol{cdietp} - 0.09\boldsymbol{lviolp} + 0.01\boldsymbol{lndfoodp} + 0.19\boldsymbol{ldebtp} + 0.08\boldsymbol{lexpp} + 0.08\boldsymbol{lsavep} - 0.16\boldsymbol{lassetsp} + 0.10\boldsymbol{lfriendsp}$$

In other words, the (log) probability of job losses were higher during lockdown and significantly lower as (log) predicted incomes rose. The (log) predicted probability of job losses were also higher for those who reported reducing children's diets, declared food as an immediate need, resorted to debt, reducing expenditures, reduced savings and relied on friends. On the other hand, it appears to be lower for those reducing HH asset bases. The coefficient plot below (Figure 26) displays the same information in graphical format.

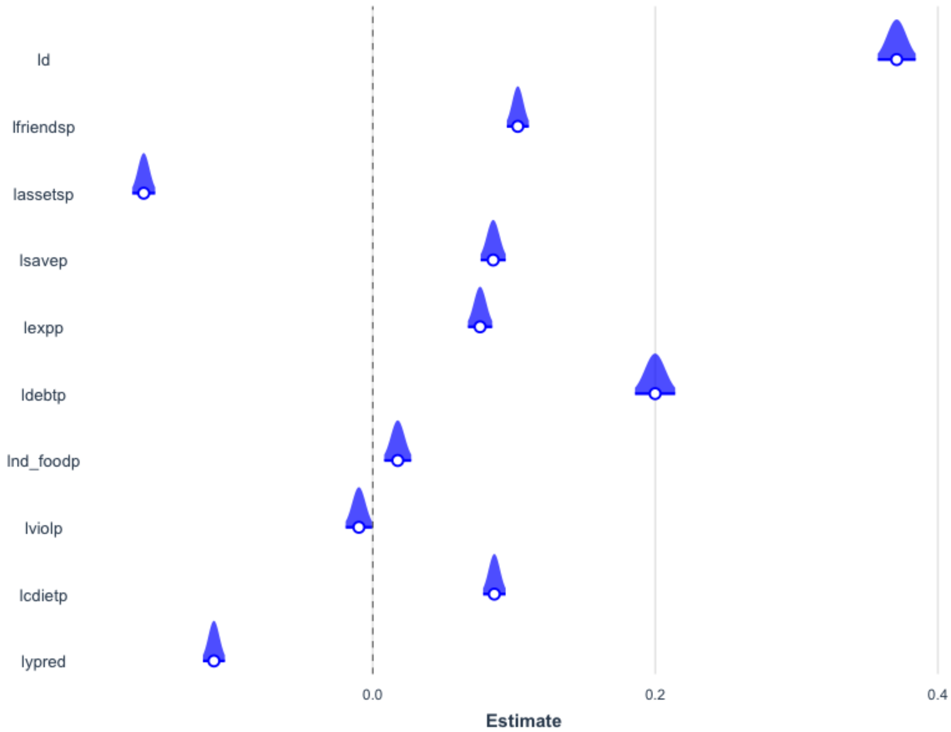

Figure 26: Within model (Fixed effects) coefficient plot of earnings losses

Reducing dietary intake of children

As regards families resorting to reducing children's diets, the following regression equation was obtained:

$$lcdietp = -0.05\boldsymbol{ld} - 0.05\boldsymbol{lypred} + 0.20\boldsymbol{learnp} + 0.25\boldsymbol{lndfoodp} + 0.05\boldsymbol{lviolp} + 0.20\boldsymbol{ldebtp} + 0.29\boldsymbol{lexpp} + 0.01lsavep + 0.10\boldsymbol{lassetsp} - 0.03\boldsymbol{lfriendsp}$$

The results suggest that reductions in children's dietary intake were a coping strategy used by households through the period under observation. It was positively correlated to earnings losses, families declaring food as an immediate need, those reporting violence, those resorting to debt, reducing expenditures, dipping into savings (not significant) and reducing assets. On the other hand, reductions in children's dietary were lower during lockdown, were lower for those with higher predicted incomes and lower for those relying on friends and relatives. The results are also shown in the coefficient plots below (Figure 27).

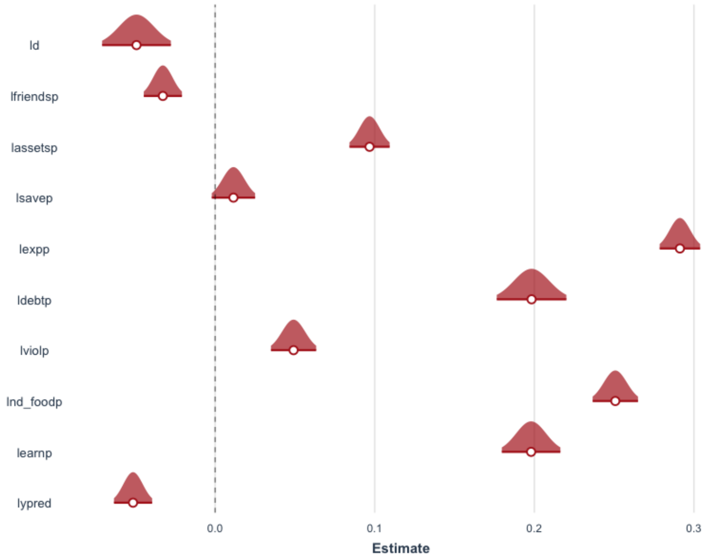

Figure 27: Within model (Fixed effects) coefficient plot of reducing children's diet

Immediate need for food

During the period under observation, a significant share of households declared food as an immediate need. The regression equation obtained is as follows:

$$lndfoodp = +0.17\boldsymbol{ld} - 0.18\boldsymbol{lypred} + 0.02\boldsymbol{learnp} + 0.17\boldsymbol{lcdietp} + 0.01\boldsymbol{lviolp} + 0.37\boldsymbol{ldebtp} - 0.07\boldsymbol{lexpp} - 0.23\boldsymbol{lsavep} - 0.003lassetsp - 0.002lfriendsp$$

These results suggest that the need for food was higher during lockdown and higher for those families losing earnings, reducing children's dietary intake, witnessing violence and resorting to increased debt. On the other hand, it was lower for those with higher earnings and those reducing expenditures or dipping into savings. It was also lower for those reducing assets and relying on friends, but these effects were not found to be significant. The coefficient plot below displays the coefficients of the regression equation (Figure 28).

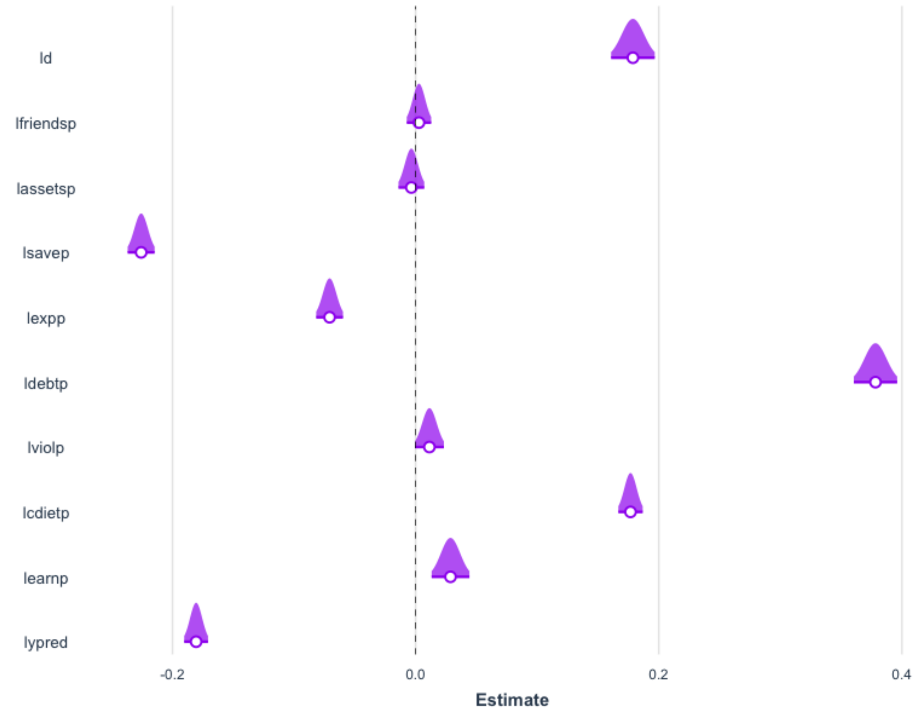

Figure 28: Within model (Fixed effects) coefficient plot of declaring food as an immediate need

Witnessing violence against women and children

The CFT also contained questions regarding witnessing violence against women and children in the community. The regression equation obtained is shown below:

$$lviolp = 0.33\boldsymbol{ld} + 0.09\boldsymbol{lypred} - 0.02\boldsymbol{learnp} + 0.03\boldsymbol{lcdietp} + 0.01lndfoodp + 0.005ldebtp - 0.05\boldsymbol{lexpp} + 0.22\boldsymbol{lsavep} + 0.08\boldsymbol{lassetsp} + 0.04\boldsymbol{lfriendsp}$$

These results suggest that witnessing violence was positively associated with the lockdown, positively associated with predicted incomes, negatively associated with loss in jobs/livelihoods, positively associated with changed dietary intake of children, negatively associated with families reducing expenditure and positively associated with reducing savings, selling household assets and relying on friends and family. Other variables were not found to be significant. The results are captured in the coefficient plot below (Figure 29).

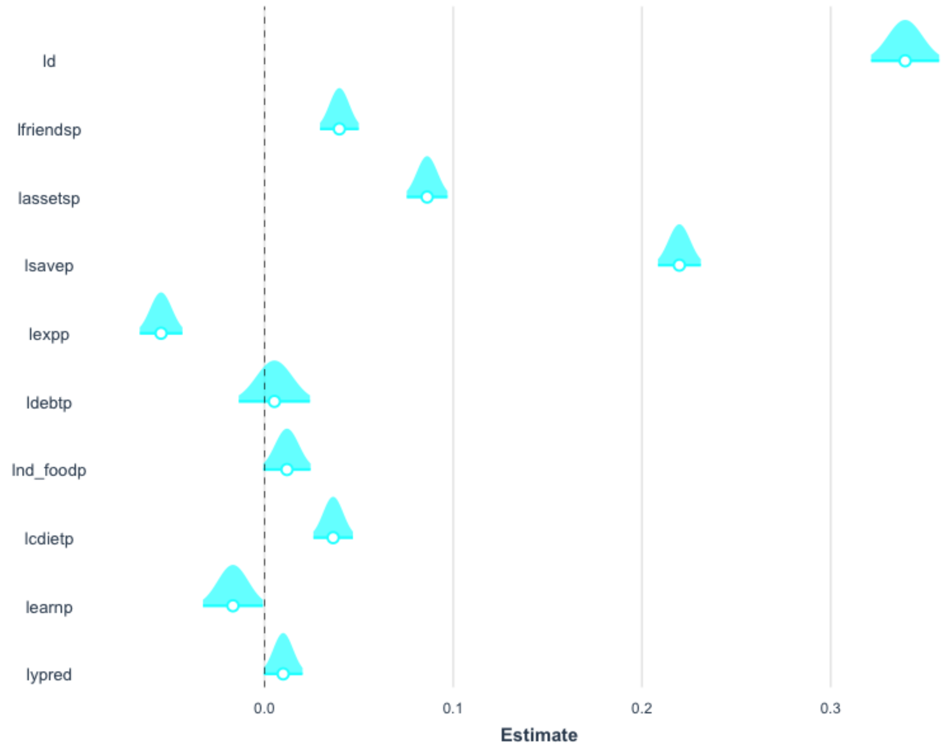

Figure 29: Within model (Fixed effects) regression plot of experiencing violence against women and children

Children not studying

The final regression model relates to children not studying. Although this has to do a lot with holidays and school closures, the fixed effect model was also useful in delineating some other factors. The fixed effect regression model yields the following equation:

$$lnostudyp = 1.56\boldsymbol{ld} - 0.001lypred + 0.10\boldsymbol{learnp} + 0.35\boldsymbol{lcdietp} + 0.10\boldsymbol{lndfoodp} + 0.01lviolp - 0.09\boldsymbol{ldebtp} + 0.15\boldsymbol{lexpp} - 0.28\boldsymbol{lsavep} - 0.17\boldsymbol{lassetsp} - 0.03\boldsymbol{lfriendsp}$$

The lockdown had the most significant impact on children's education owing to school closures and narrow outreach of distance learning. Furthermore, children not studying was also significantly and positively associated with jobs/livelihood losses, reductions in children's dietary intakes, households declaring food as an immediate need and reduction of household expenditure. As before, the coefficients are plotted below (Figure 30).

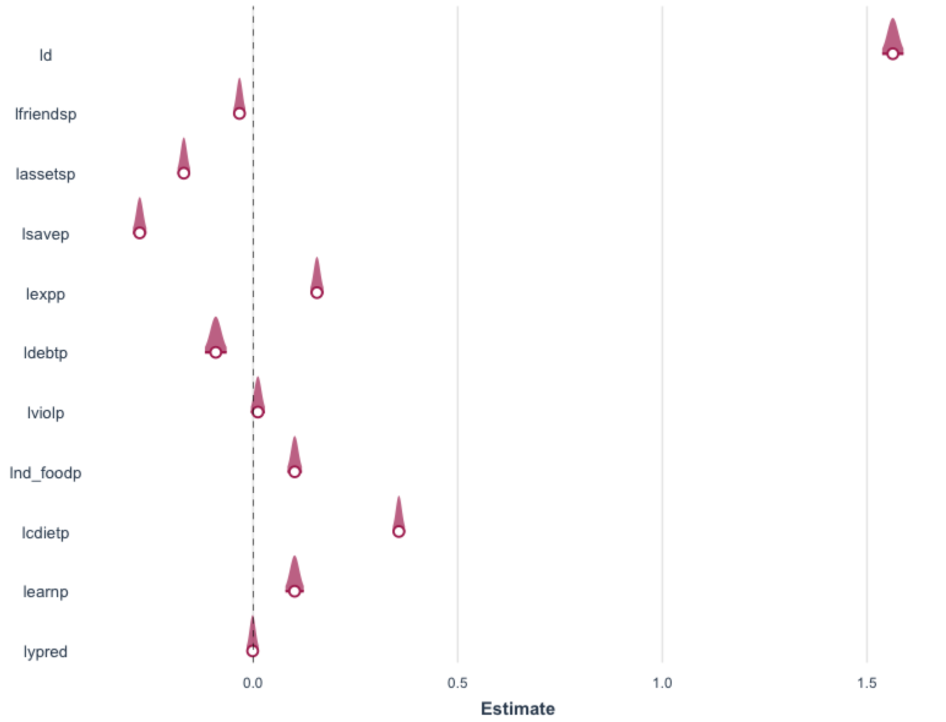

Figure 30: Within model (Fixed effects) coefficient plot of children not studying

Random effects model (between model)

The between (random effects) model uses, in addition to the variables above the following 19 variables are used for model specification (Table 8):

Table 9: Variables used in random effects models

Variable Name	Description	Mean (actual variable) over 6 rounds
lage	Log age of respondent	36.7
Pro_ETHOSProvince2	Province 2 dummy	n.a
Pro_ETHOSProvince3	Bagmati Province dummy	n.a
Pro_ETHOSProvince4	Gandaki Province dummy	n.a
Pro_ETHOSProvince5	Lumbini Province dummy	n.a
Pro_ETHOSProvince6	Karnali Province dummy	n.a
Pro_ETHOSProvince7	Sudurpaschim Province dummy	n.a
typeUrban Mun	Municipality type urban municipality	n.a
typeRural Mun	Municipality type rural municipality	n.a
typeSub Metro	Municipality type sub metropolitan	n.a
wrk_agr	Dummy for working in agriculture	72%
wrk_dwage	Dummy for working as daily wage earner	21%
wrk_pvt	Dummy for working in private sector	6%
wrk_serv	Dummy for working in services sector	29%
eduhd	Education level of head of HH in years	8 years
disab	Dummy for PWD in household	14%
femhd	Dummy for female headed household	21.4%
lsratio	Log of ratio of number of children to total HH size	39.2%
dalit	Dummy for Dalit HH	10.5%
Note: Pro_ETHOSProvince 1 is the comparator for Provinces		

typeMetropolitan is the comparator for types These two do not appear in the regressions to avoid the dummy variable trap (collinearity) None of these variables change over rounds – hence they are assumed to be fixed

Job losses

The first model examines jobs/livelihood losses. The coefficient plot Figure 31 shows that Dalit households, households with a larger number of children relative to HH size, female headed households, households with a family member working in traditional agriculture or for daily wages and households with higher predicted incomes are likely to experience lower jobs/livelihood losses in aggregate over the period under observation. Furthermore, in comparison to metropolitan type residences, sub-metro cities, rural and urban municipalities are likely to experience higher job losses. Relative to Province 1, Province 2 and Bagmati are predicted to have the highest rate of job losses, though all the provinces show significant job losses. Finally, the fixed effects variables seen earlier are held at individual mean levels and have the same impact on jobs/livelihood losses: higher predicted income levels would tend to reduce the probability of jobs/livelihood losses.

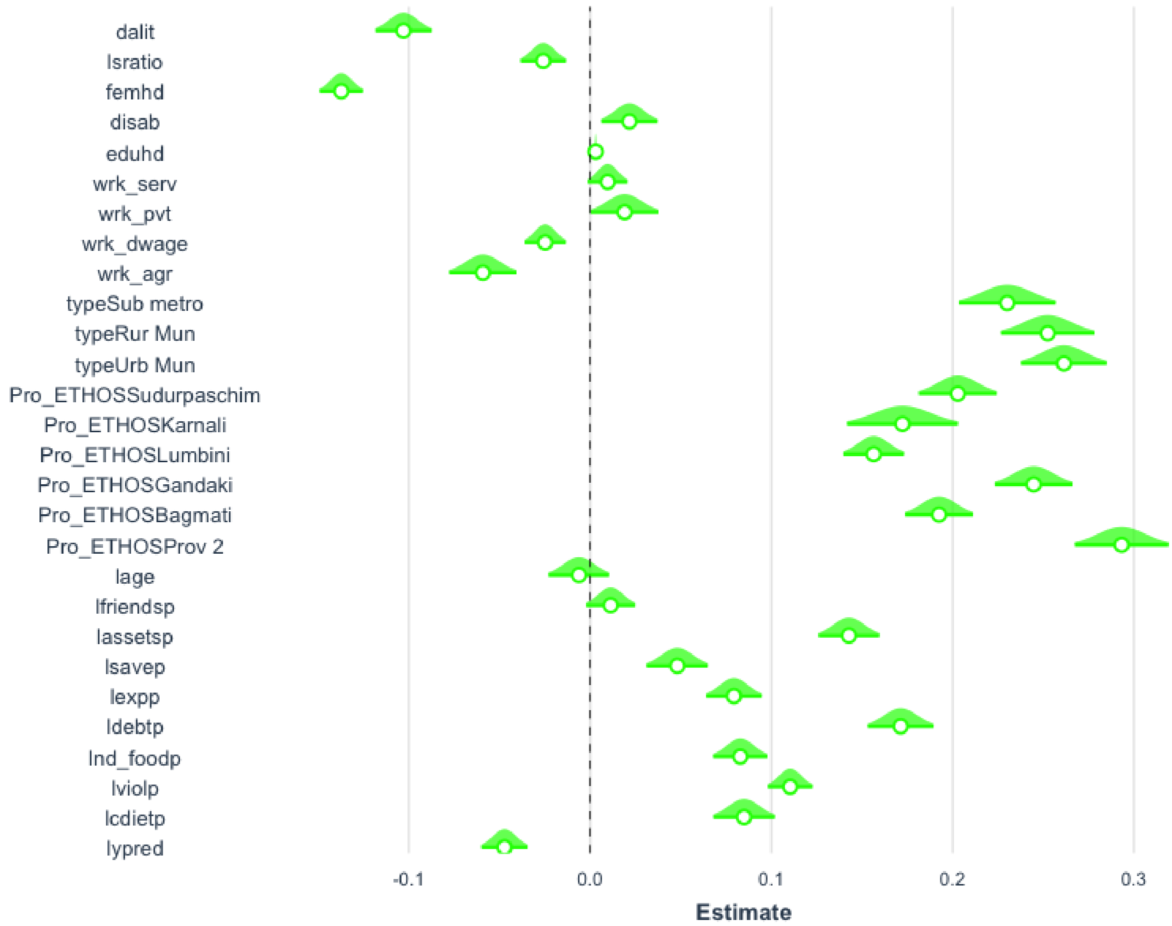

Figure 31: Between model (Random effects) coefficient plot of earnings losses

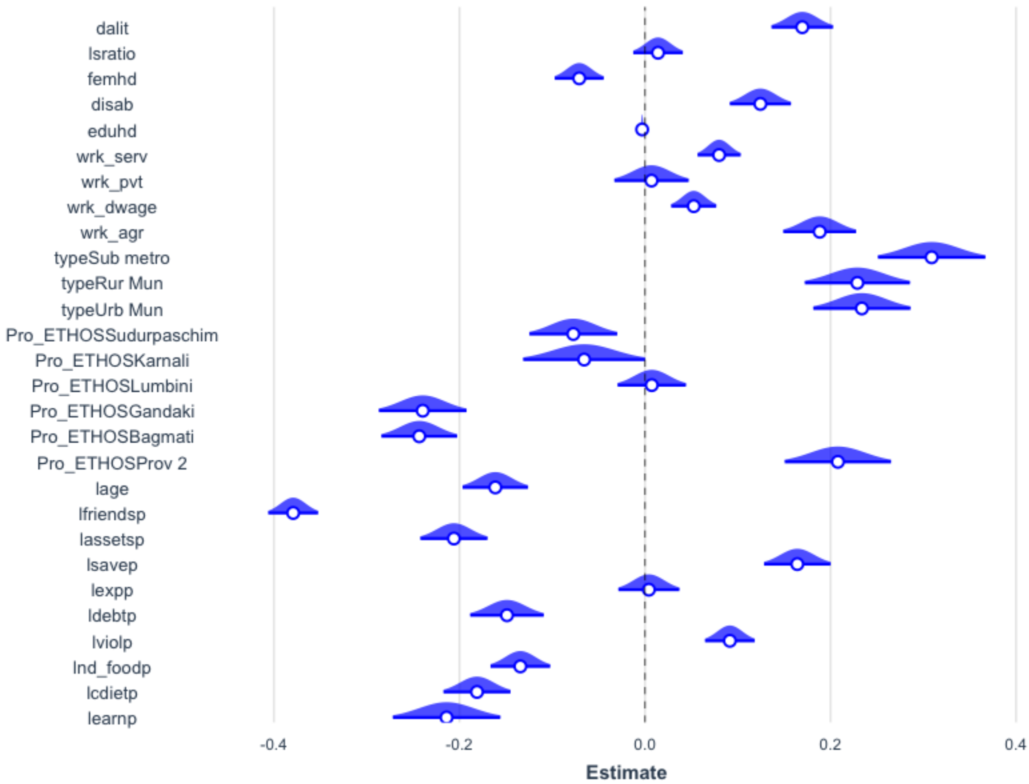

Figure 32: Between model (Random effects) coefficient plot of income distributions

Income distribution

The between effects model for income distributions (Figure 32) shows that Dalit headed households had a higher probability of income losses as did households with a higher ratio of children to total household sizes (though not significantly different from zero as the distribution overlaps the vertical zero line). Female headed households had a lower level of predicted incomes while households with PWD had a higher level of predicted incomes. Households where the head had a higher level of education tended to have a lower level of predicted incomes. Households with members working in agriculture, daily wages and services had a higher predicted level of incomes but the same is not true for the private sector. In terms of geographic residential factors, households in both urban and rural municipalities have higher incomes but lower than those in sub-metropolitan areas. Bagmati and Gandaki were predicted to have the lowest predicted income distributions while Province 2 had the highest. Respondents with higher ages tended to have lower predicted income levels. Households with a strong reliance on friends and relatives were predicted to have low income distributions as were households resorting to increased debt and selling assets. Similarly households with increased probability of reducing children's diets, higher probability of declaring food as an immediate need and those with a higher probability of job losses were also predicted to have lower income levels.

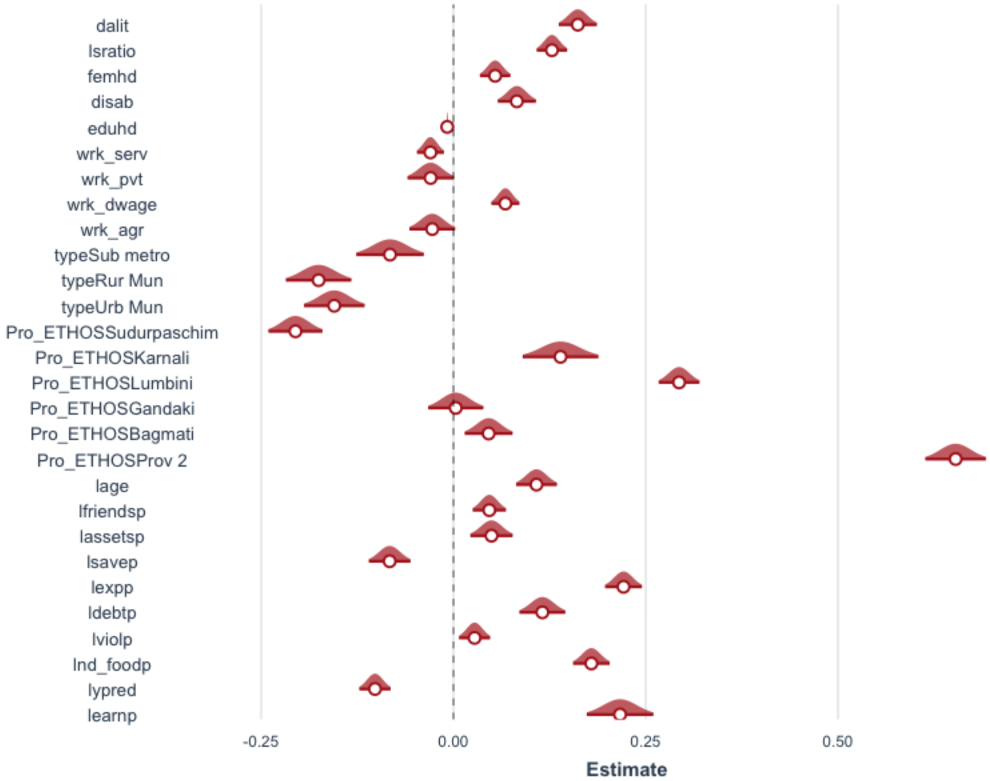

Figure 33: Between model (Random effects) coefficient plot of reduced dietary intake of children

Reducing dietary intake for children

A significant number of households reported reducing children's dietary intake. These varied by characteristics of the respondents household. From the coefficient plot in Figure 33, we can see that respondents in Province 2 were the most likely to report reducing dietary intake for children and to a lesser extent respondents from Karnali and Lumbini. On the other hand, respondents from Sudurpaschim were least likely to report reducing children's dietary intake. Similarly respondents from urban municipalities, rural municipalities and sub-metro areas were less likely to report reductions in children's dietary intake. Households with a person with disability living with them, households with a higher number of children relative to family size, female headed households and Dalit households were more likely to report reductions in their children's dietary intake controlling for all other variables. Households where the respondent is older, incurring increased debt, relying on friends and family, selling assets, declaring food as an immediate need or witnessing violence were more likely to report reducing children's dietary intake. Households declaring higher levels of job losses were more likely to report reducing children's dietary intake while those with higher predicted incomes were less likely.

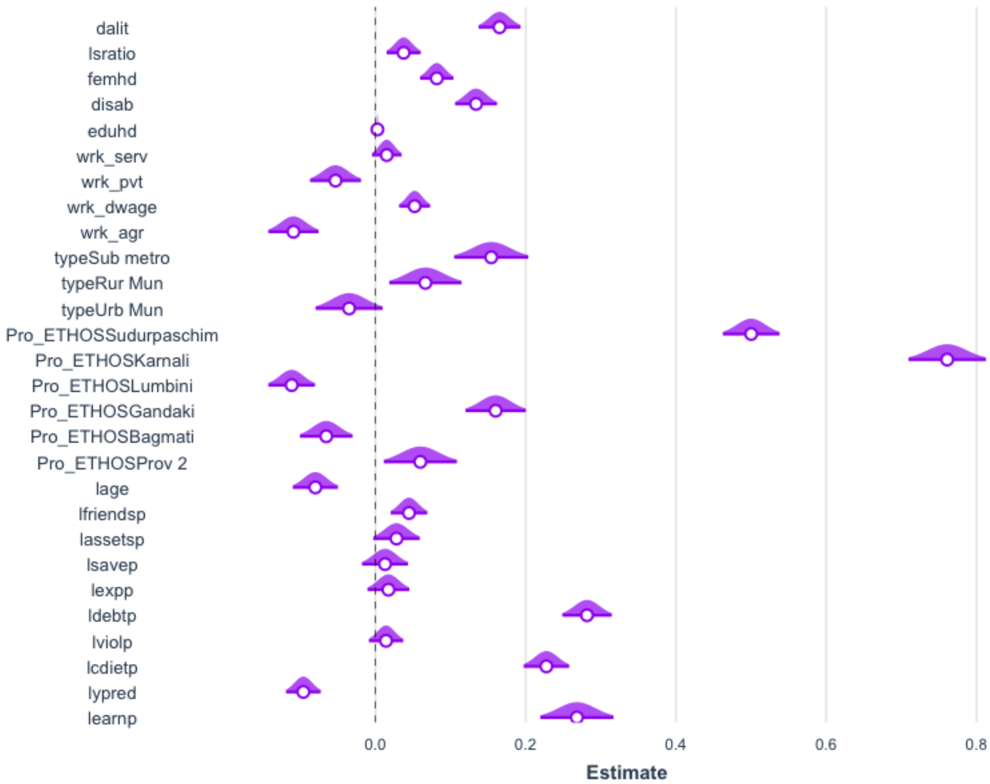

Figure 34: Between model (Random effects) coefficient plot of declaring food as an immediate need

Food as an immediate need

Households declaring food as an immediate need followed somewhat similar patterns as households reporting reduced dietary intake for children with some exceptions. The coefficient plots from the regression equations are shown in Figure 34. Dalit households, female headed households, households with a larger share of children relative to household size, and households with at least 1 person with a disability living with them were more likely to declare food as an immediate need. Similarly, households with members working for daily wages are more likely to report food as an immediate need. On the other hand, households with members working in the private sector or agriculture were less likely to report reducing children's dietary intake. Households from rural and urban municipalities were more likely to report needing food immediately. In terms of provinces, Sudurpaschim and Karnali residents were most likely to report food as an immediate need. Households from Gandaki and Province 2 were also more likely to report food as an immediate need. On the other hand, respondents from Bagmati and Lumbini province were less likely to report food as an immediate need. Respondents with a higher predicted income level were less likely to report food as an immediate need while households with higher probability of job losses, higher probability of relying on debt, reducing assets, relying on friends and reducing children's dietary intake were more likely to report food as an immediate need.

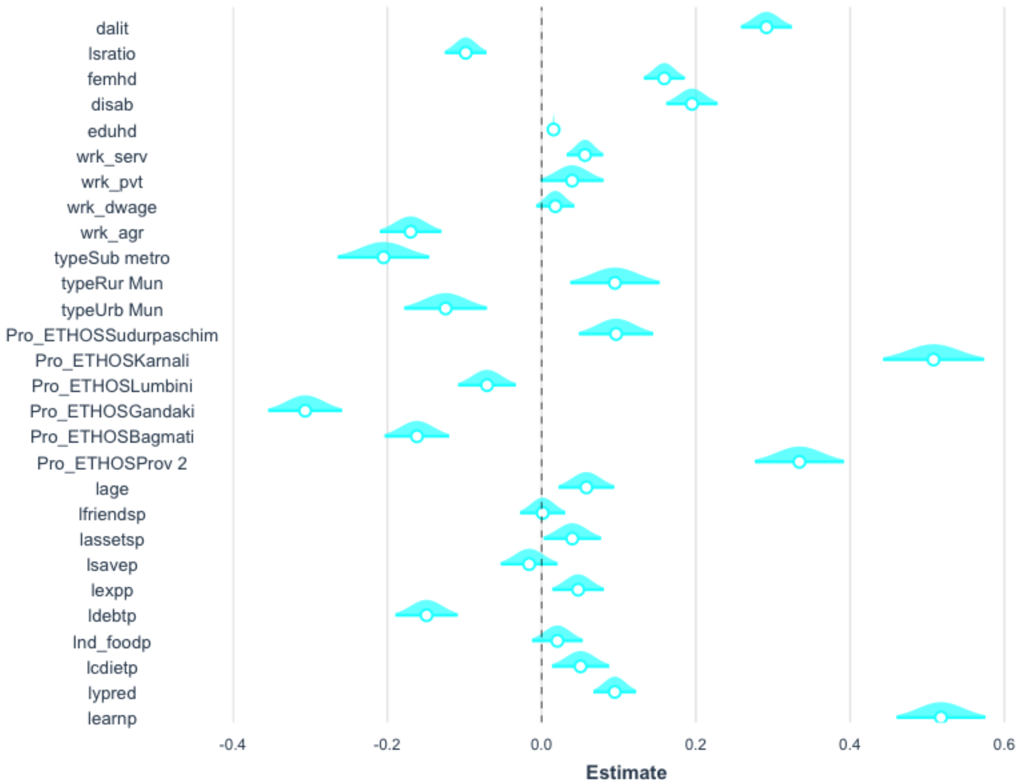

Figure 35: Between model (Random effects) coefficient plot of reporting witnessing violence against women and children

Witnessing violence against women and children

With respect to reporting violence against women and children, Dalit headed households, female headed households, households with at least one person with a disability living with them and households whose heads have a higher level of education are more likely to report witnessing violence against women and children (Figure 35). Households with a larger share of children relative to household size are less likely to report witnessing violence. Respondents from Province 2, those with a higher probability of job losses and respondents from Karnali were the most likely to report witnessing violence against women and children. Respondents from Gandaki and sub-metropolitan cities as well as households with members working in traditional agriculture were the least likely to report witnessing violence against women and children.

As reported in the CFT round 6 results, domestic violence, sexual abuse and psychological or emotion abuse were the main protection risks facing women and children. Respondents reported their main concern for children was falling into bad company and lack of daily care and supervision. Respondents consistently reported anger and aggressive outbursts from their children consistently between October and Jan 2021 – even after the lockdown had been lifted.

Children not studying

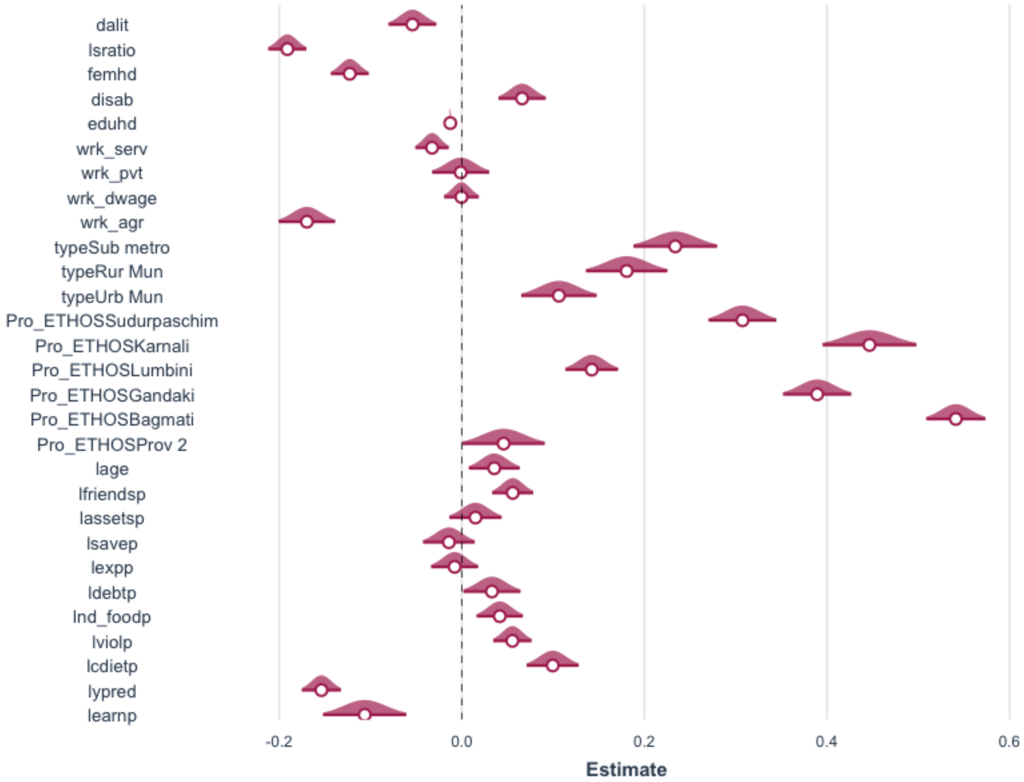

Figure 36: Between model (Random effects) coefficient plot of children not studying

In terms of the probability of children not studying (reported), the following factors were responsible for reducing the probability that children were not studying (Figure 36): Dalit households, households with a higher share of children relative to family size, female headed households, households where the education level of the head of household is higher, households with family members working in services, households with family members working in traditional agriculture, families with a higher level of predicted income as well as households with a higher probability of job losses. All other factors were responsible for increasing the likelihood of children not studying. In particular, respondents from Bagmati and Karnali were most likely to report children not studying though all provinces had a significantly positive impact on the probability of children not studying as did respondents from sub-metro areas, urban municipalities and rural municipalities.

Frequency of shocks (incidence analysis)

The panel data framework also allows tracking the number of times respondents reported shocks of various kinds. The resulting data are 'count data'[10] and serve to highlight the frequency of shocks (incidence rate). The results are summarized in Table 10 below – the numbers in parenthesis denote percentages.

Table 10: Frequency of shocks

Frequency of shocks	Jobs loss	Income <10K	Reducing dietary intake for children	Struggling for food daily	Declaring food as an immediate need	Witnessing violence against women and children
0	513 (10%)	820 (16%)	2029 (39%)	3401(66%)	1790 (35%)	3963 (77%)
1	821 (16%)	683 (13%)	1386 (27%)	984 (19%)	1233 (24%)	788 (15%)
2	1117 (22%)	844 (16%)	774 (15%)	504 (10%)	898 (17%)	249 (5%)
3	1066 (21%)	934 (18%)	511 (10%)	212 (4%)	619 (12%)	107 (2%)
4	950 (18%)	913 (18%)	332 (6%)	79 (2%)	352 (7%)	47 (1%)
5	523 (10%)	769 (15%)	143 (3%)	--	191 (4%)	20 (<1%)
6	190 (4%)	217 (4%)	5 (<1%)	--	97 (2%)	6 (<1%)
N=5180. Due to rounding error the per cent totals may not be exactly 100%						

The findings suggest that a significant proportion of respondents reported numerous shocks over the 6 waves/rounds. In particular:

- 10% reported no job/livelihood losses over all rounds. 90% reported job losses more than 1 time. 63% reported job losses 2, 3 or 4 times. 14% reported job losses 5 or 6 times.
- 16% reported not having income less than NPR 10K/month over all rounds. 84% reported monthly household incomes less than NPR 10K more than once. 67% reported monthly incomes less than 10K 2, 3, 4 or 5 times. 4% reported monthly household incomes below 10K across all the rounds (6 times). 19% reported monthly income less than NPR 10K 5 or 6 times.
- 39% reported not having to reduce children's diet in any of the rounds. 61% reported having to reduce their children's diet at least one time. 52% reported having to reduce children's diet 2, 3 or 4 times.
- 66% reported not having to struggle for food in any of the rounds while 34% reported having to struggle for food in at least 1 round. This question was asked only for 4 rounds/waves and hence the maximum value is 4. 2% of households reported struggling for food 4 times.
- 35% reported not needing food immediately. 65% reported food as an immediate top three need at least in 1 round. 53% reported an immediate need for food 1, 2 or 3 times.
- 77% reported not witnessing any violence against women and children. 23% reported witnessing violence against women and children at least once.

These outcomes are correlated and vary by background characteristics such as coping strategies, gender, education level of the head of household, number of children and so on. A Poisson generalized linear model (appropriate for 'count' data)

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[10] Count data are most often assumed to be generated by a Poisson process in statistics hence the use of a Poisson generalized linear model for the analysis. This model assumes that observed counts are generated by a Poisson process which is affected by covariates chosen for the analyses.

is used to tease out the significant variables. A description of the 28 variables is given below:

1. save: # of times household reported reducing savings
2. exp: # of times household reported reducing expenditures
3. debt: # of times household reported incurring debt
4. viol: # of times household reported witnessing violence against women and children
5. cdiet: # of times household reported reducing children's dietary intake
6. ndfood: # of times household reported food as an immediate need
7. strf: # of times household reported struggling for food
8. ssa: # of times household reported receiving any social security allowances
9. fina: # of times household reported receiving any form of assistance from the government
10. wrk_dwage: Dummy for household reporting a member working for daily wages
11. wrk_agr: Dummy for household reporting a member working in traditional agriculture
12. q001_c: Age of respondent (centred around mean)
13. kids_c: Number of children in household (centred about mean)
14. gender: Gender of respondent (1=Female, 2=Male)
15. femhd: Dummy for female headed household
16. eduhd_c: Education level of head of household in years (centred about mean)
17. disab: Dummy for household having at least one person with disability
18. Pro_ETHOS07: Dummy for respondent belonging to Sudurpaschim
19. Pro_ETHOS06: Dummy for respondent belonging to Karnali
20. Pro_ETHOS05: Dummy for respondent belonging to Lumbini
21. Pro_ETHOS04: Dummy for respondent belonging to Gandaki
22. Pro_ETHOS03: Dummy for respondent belonging to Bagmati
23. Pro_ETHOS02: Dummy for respondent belonging to Province 2
24. typeSub metro: Dummy for respondent living in sub metropolitan province
25. typeRur mun: Dummy for respondent living in rural municipality
26. typeUrb mun: Dummy for respondent living in urban municipality
27. poor: # of times household reported monthly income less than NPR 10K
28. earn: # of times household reported losing jobs/livelihoods

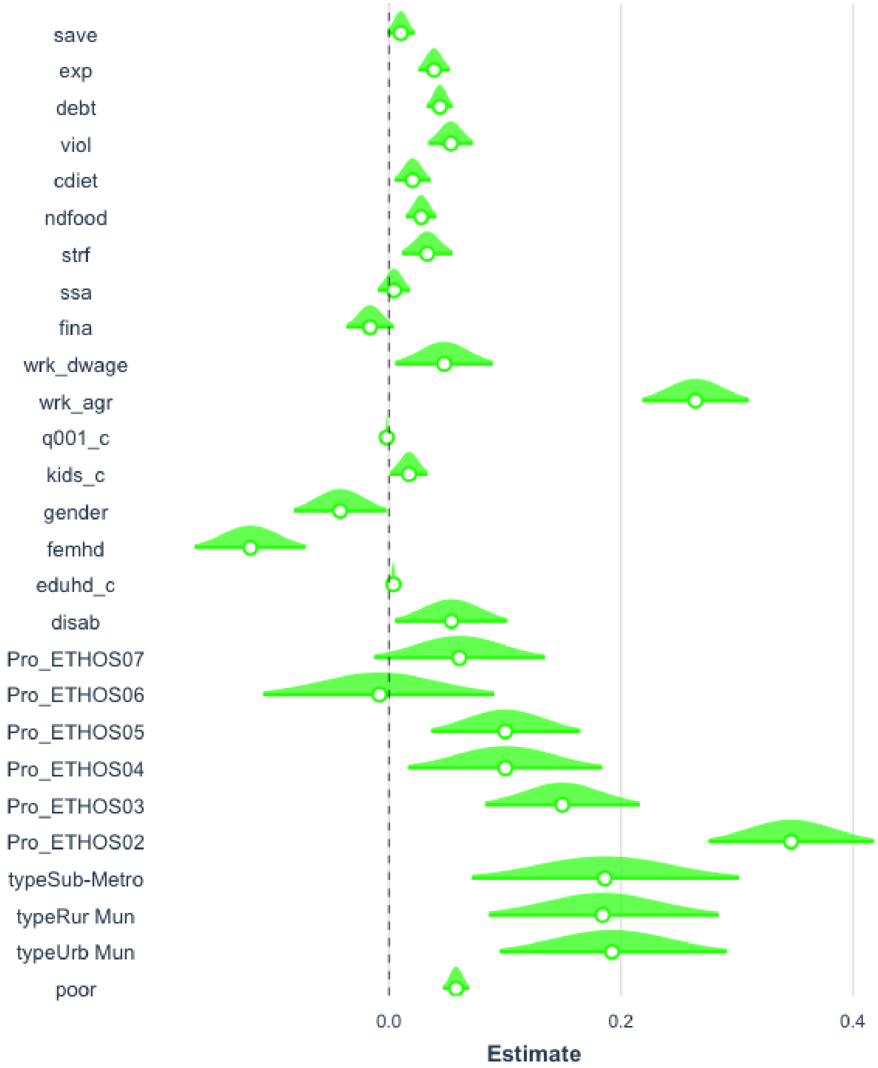

Figure 37: Coefficient plot of # of times job losses reported by respondents

Frequency of job losses

For the frequency of reported job losses, the coefficient plots are shown in Figure 37. Except for the frequency of receiving government assistance, frequency of receiving social security allowances, being from Provinces 6 and 7, all the variables are significantly different from zero. Female headed households, older respondents and male respondents were more likely to report lower frequency of job losses. Respondents with family members working in agriculture and from Province 2 were the most likely to report highest frequency of job losses. Higher frequency of job losses were also associated with increased episodes of households reporting monthly income less than NPR 10K, living in sub-metro, urban and rural municipalities (in relation to metropolitan municipalities), living in Provinces 3, 4 and 5, households with at least one person with disability, households with a higher level of education of the head, households with a member working for daily wages, households with a higher frequency of reporting food as an immediate need, households reporting a higher frequency of struggling for food, households with a higher frequency of reducing children's dietary intake, households reporting witnessing violence more frequently and households with a higher frequency of incurring debt or reducing expenditures.

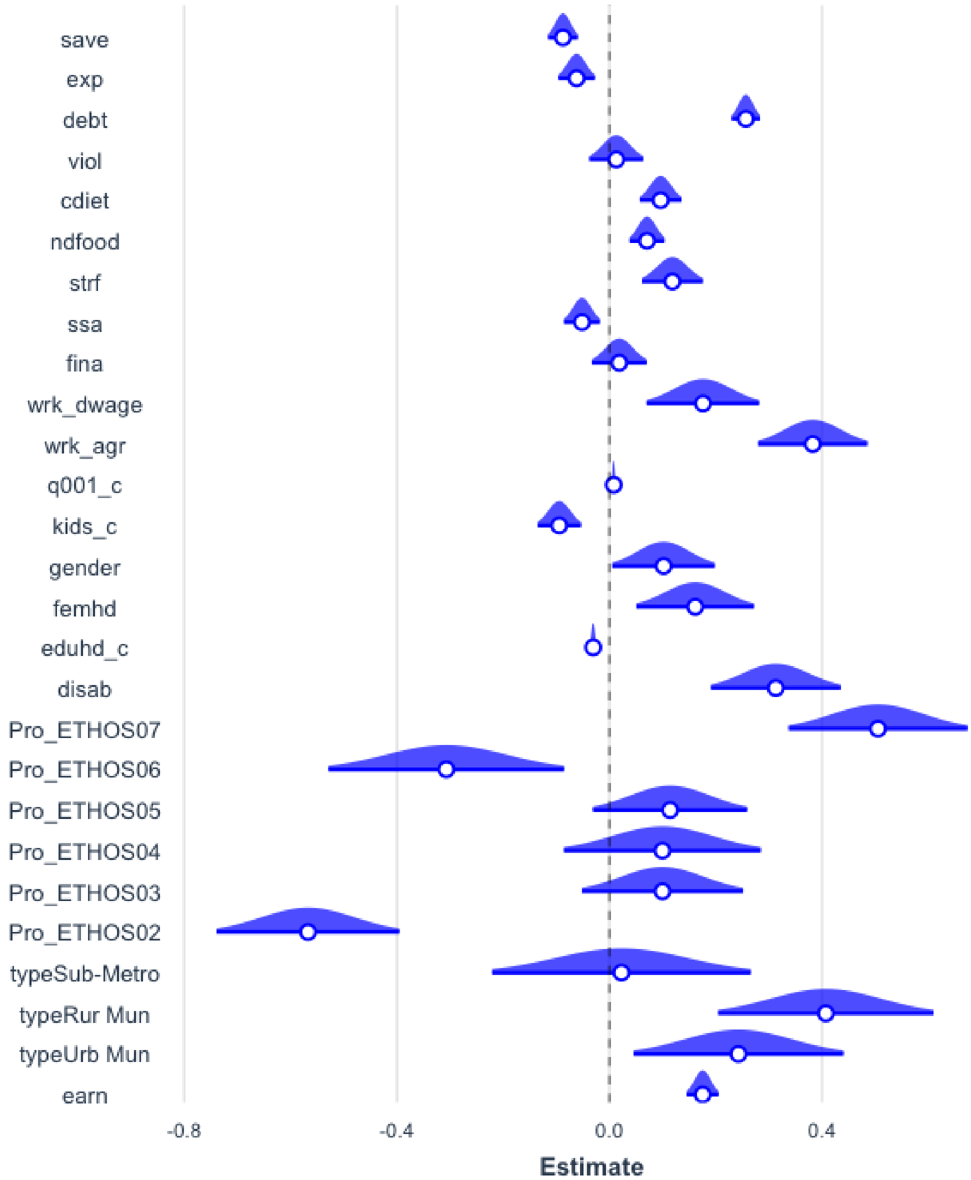

Figure 38: Coefficient plot of # of times HH earnings<10K

Frequency of HH reporting monthly income less than NPR 10K

Factors responsible for reducing the frequency of households reporting monthly incomes less than NPR 10K were (Figure 38): being from Province 2, being from Province 6, households with a higher level of education of the head, households with more children, households with a higher frequency of receiving social security allowances, households reporting reducing expenditures more frequently and households reporting a higher frequency of reducing savings. Variables that were not found to be significant include being from Provinces 3, 4 or 5, living in sub-metropolitan municipalities, receiving any assistance from the government, and reporting a higher frequency of witnessing violence. All other variables increased the frequency of a household reporting monthly incomes less than NPR 10K – the most significant being living in a rural municipality, working in traditional agriculture and being from Sudurpaschim.

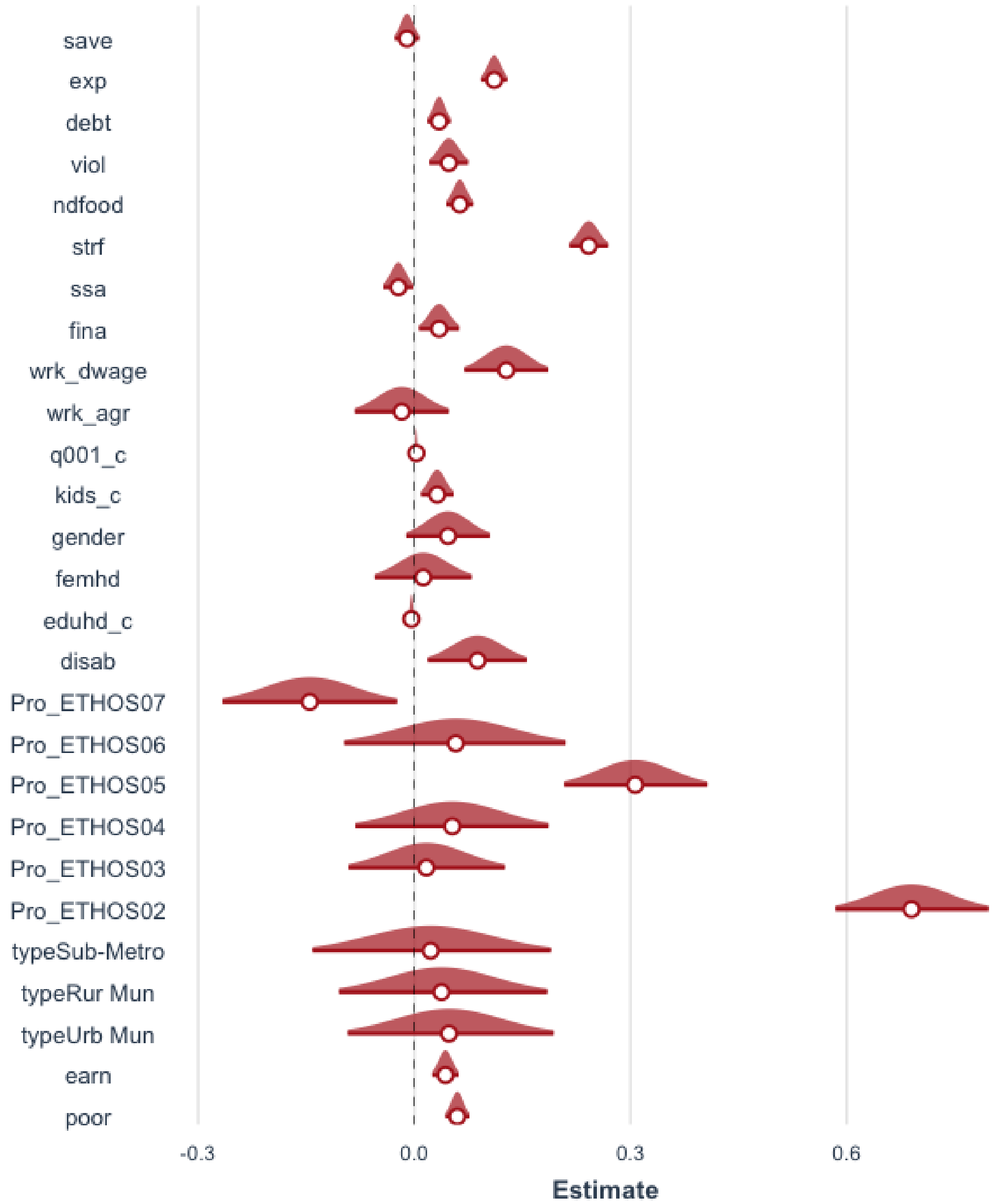

Figure 39: Coefficient plot of # of times reduced diet for children

Frequency of reducing children's dietary intake

With respect to the frequency of reducing children's diets Figure 39 demonstrates that variables that bore no influence were the type of municipality, being from provinces Bagmati, Gandaki and Karnali, female headed households, gender of respondent, households with family members in agriculture, and those with a higher frequency of reducing savings. Factors that increased the frequency of reducing children's dietary intake were households with a higher frequency of having monthly incomes less than NPR 10K, households with a higher frequency of job losses, households from Province 2 and Lumbini, households with at least one person with disability living with them, households with a family member working for daily wages and household with a higher frequency of struggling for food, needing food immediately, witnessing violence against women and children, incurring debt and reducing expenditures. Factors that were associated with a decrease in the frequency of reducing dietary intake of children were the frequency of receiving social security allowances and the education level of the head of household.

Frequency of struggling for food

Figure 40: Coefficient plot of # of times struggling for food reported by respondent

The number of times a household struggled for food (Figure 40) is positively correlated to the number of times households declared monthly incomes below NPR 10K, the number of times households reported losing jobs, the number of times household declared food as an immediate need, the number of times households reported reducing children's dietary intake, the number of times households incurred debt or reduced expenditures and older respondents. It was also positively correlated to respondents being male, and female headed households. Respondents from Province 2, Bagmati, Gandaki, Lumbini and Sudurpaschim were likely to report a lower frequency of struggling for food as were households where the head had a higher level of education as well as households with a higher frequency of dipping into savings. All other variables were not significant in explaining variations in the frequency of households struggling for food.

Frequency of witnessing violence against women and children

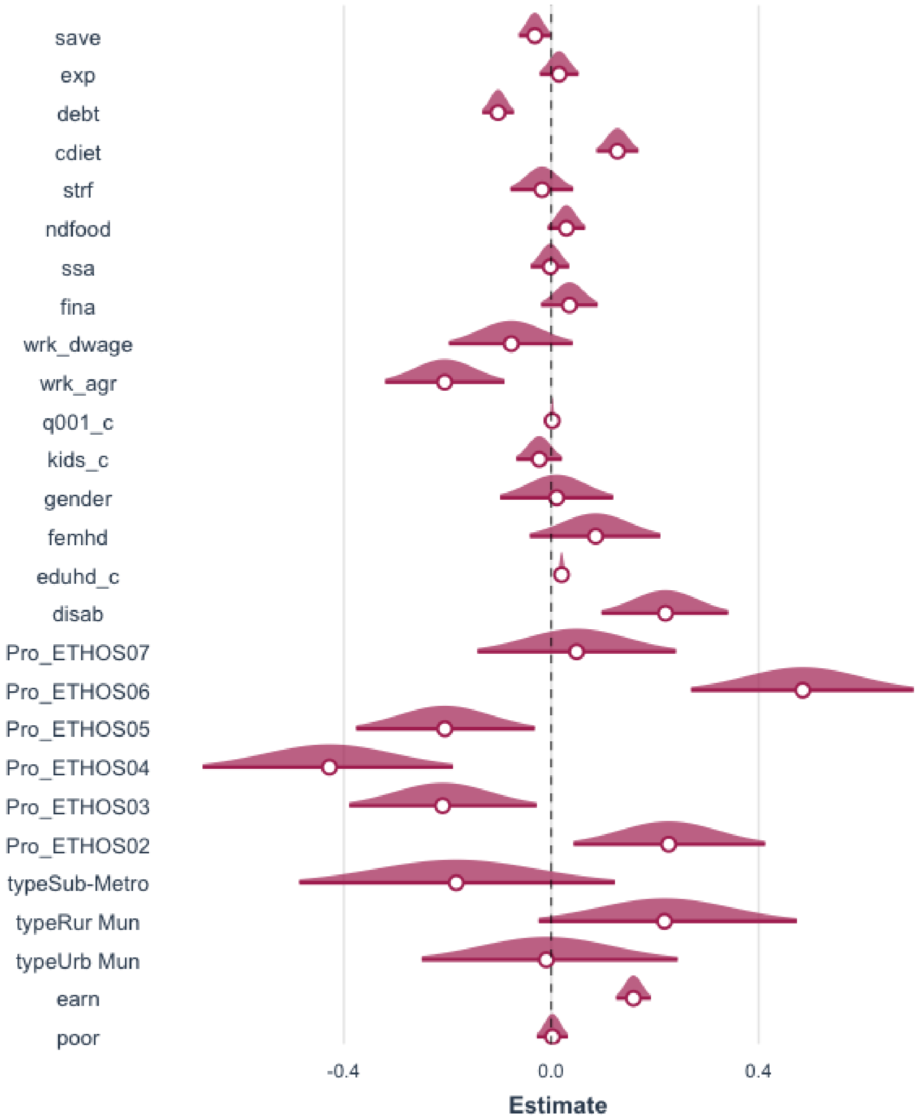

Figure 41: Coefficient plot of # of times HH reported witnessing violence against women and children

The frequency of witnessing violence against women and children (Figure 41) was found to be significantly higher for households reporting a higher frequency of job losses, households living in rural municipalities, households from Province 2 and Karnali, households with at least one person with a disability living with them and households where the education level of the head of households was higher. On the other hand, households from Bagmati, Gandaki and Lumbini, households with a family member working in traditional agriculture and households with a higher frequency of incurring debt were expected to have a lower frequency of witnessing violence against women and children.

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