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ESSAYS ON ECONOMIC DEVELOPMENT AND ENVIRONMENTAL SUSTAINABILITY

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ESSAYS ON ECONOMIC DEVELOPMENT AND ENVIRONMENTAL SUSTAINABILITY

by

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Submitted to School of Economics in partial fulfilment of the requirements for the Degree of Doctor of Philosophy in Economics

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ABSTRACT: The first chapter is a randomized controlled trial study that uses loss framing and information nudges to increase secondary school attendance in Bangladesh. Conditional cash transfers (CCTs) have become one of the most common policy interventions to increase school attendance, but the cost-effectiveness of such interventions has not attracted the attention it deserves. Hence, in addition to a standard CCT implementation, our rich unique dataset on daily attendance allows us to experimentally study two potential ways to improve the cost-effectiveness of school attendance interventions: (i) SMS information nudges and (ii) loss framing in CCTs. The former provides school attendance information to parents and the latter exploits the endowment effect. Consistent with the existing literature, CCT intervention significantly increases school attendance. Though the difference between gain and loss framing is not statistically significant, the point estimate of the Loss treatment is consistently higher than that of the Gain treatment. The SMS treatment has a modest impact on school attendance but the overall cost of treatment is low. We also find diminishing marginal impact of cash transfer amount on attendance, indicating that the intensive margin matters. Thus, both loss framing and SMS nudges can be considered as alternative cost-effective approaches to promote attendance in schools in developing and less developed economies.

In the second chapter, I study the causal impact of alcohol consumption on incidence of intimate partner violence in the Indian context. A study by the World Health Organization shows that about 35% of women in the world have been victims of physical or sexual intimate partner violence in their lifetime. Using an overidentified model where I exploit the spatial variation in alcohol ban and minimum legal drinking age across states in India to instrument for the husband's alcohol consumption, I find that alcohol consumption by the

husband increases incidence of less severe physical violence by 55 percentage points and severe physical violence for women by 23.6 percentage points, and also has negative consequences on women empowerment in general. I further show that the results are not driven by worse gender attitudes in states where alcohol is allowed. A heterogeneity analysis reveals that there is a vicious cycle of intimate partner violence whereby individuals who are the most vulnerable in terms of having previous exposure to domestic abuse or residing in poorly constructed houses are often the victims.

The third chapter explores the causal impact of the mid day meal program on parental investment in education for primary school going children in India. Using the first round of the Indian Human Development Survey (IHDS) and exploiting the staggered implementation of the mid day meal program across different states in India, we find that the amount spent on school fees reduces significantly by 16 percent for children who are eligible to receive the mid day meal. The significant decrease in school fees can, in part, be attributed to transfer of children from private to government schools. We further find that such transfers do not lead to any improvement in learning or health outcomes. However, there is no evidence of gender discrimination in school expenditures that might adversely affect the girl child.

The fourth chapter outlines Singapore's major sustainability challenges and its policy response in the areas of land use, transportation, waste management, water, and energy. We review the current and past Concept Plans from the perspective of sustainable land use and provide an overview of transportation policy in Singapore. We also examine Singapore's policies to manage increasing wastes and review the four tap water management plan. Finally, we look at various initiatives by the government for sustainable use of energy. We discuss the opportunities that new technologies will bring about and the role that Singapore can play in building a sustainable city.

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1 Conditional Cash Transfer, Loss Framing, and SMS Nudges: Evidence from a Randomized Field Experiment in Bangladesh[1]

1.1 Introduction

Conditional cash transfers (CCTs) have gained popularity since the inception of Progresa in 1997 in Mexico.[2] CCT programs have been implemented with various aims such as increasing demand for food (Attanasio and Lechene, 2010), empowering women (Almås et al., 2018), improving health, and reducing neonatal and infant mortality (Barber and Gertler, 2010), child marriage (Buchmann et al., 2017), and even deforestation (Jayachandran et al., 2017). As of 2014, they had spread to about 70 countries (Lindert, 2014) with governments engaging as high as 1.2 percent of their GDP on CCT programs (for example, the Bobo Desarrollo Humano program in Ecuador). While the details of the implementation vary substantially across programs, CCT interventions typically aim at promoting investment in human capital in the form of education, health, and/or nutrition. These programs require beneficiary households to fulfill certain conditions, such as regular school attendance of school-age children or regular visits to health clinics, to receive cash transfers. Even though the specific aims

[1]This paper has been co-authored with Professor Tomoki Fujii (Singapore Management University, Professor Christine Ho (Singapore Management University) and Professor Abu S. Shonchoy (Florida International University). We would like to thank Joseph Altonji, James Berry, Barbara Biasi, Gaurav Dutt, Maulik Jagnani, Hisaki Kono, Takashi Kurosaki, Costas Meghir, Rohini Pande, Rebecca Thornton, and seminar attendees at Monash and Yale for insightful comments and suggestions. We also thank Akshat Daga, Alekhyo Roychowdhury, Ishaan Malik, and Snehal Modi for research assistance. We benefited from data collection support from MOMODa Foundation and technical support from the Metakave team to automate the process of sending SMS. Finally, we express our sincere gratitude to the participating schools, the students, their parents, and the teachers. Funding from the Shirin Fozdar Foundation and Singapore Ministry of Education Academic Research Fund Tier 1 Grant (17-C244-SMU-004) and Japan Center for Economic Research are gratefully acknowledged. This research was approved by the Singapore Management University Institutional Review Board (IRB-16-082-A092-C2(220)). The trial in this study was registered in the AEA RCT registry under AEARCTR-0002373. All mistakes remain ours.

[2]Progresa was later renamed to Oportunidades in 2001 and Prospera in 2014 before being terminated in 2019. Parker and Todd (2017) provide a review of Progresa/Oportunidades.

of the programs vary, one of the main objectives of these programs has been to suppress intergenerational transmission of poverty by breaking the vicious cycle of low human capital investment, through the use of cash incentive to promote desirable behavior.

Studies have shown that the Progresa program and its successors led to a significant positive impact on school enrollment for all grades (Behrman et al., 2009; Dubois et al., 2012; Shultz, 2004; Todd and Wolpin, 2006). With the success of Progresa, CCT has become a popular policy tool and has been implemented in Latin America and other developing regions over the last two decades. CCT programs have thus promoted school enrollment in Brazil (Glewwe and Kassouf, 2012), Bangladesh (Khandker et al., 2003), Ecuador (Schady et al., 2008), and Colombia (Attanasio et al., 2010), among others, even though the short-term impact on student learning as measured by test scores tends to be small and insignificant at best.[3]

Our study relates to a large body of literature on CCTs. Some programs that are CCT on paper may look more like unconditional cash transfers (UCTs) when there is poor monitoring and enforcement of conditions.[4] We focus on CCTs instead of unconditional cash transfers (UCTs) because the conditionality of CCTs may be important in incentivizing parents to send their children to school. Existing studies indeed indicate that conditionality is essential when raising school attendance is an important policy goal (Baird et al., 2011; Martinelli and Parker, 2003; De Brauw and Hoddinott, 2011). This could be particularly relevant in agricultural areas, where parents may be myopic and value field work or early marriage over education. How the conditions are written and enforced is, therefore, an important consideration in our study. In particular, we design our field experiment with the objective of improving school attendance in a cost-effective

[3]See Fiszbein and Schady (2009) for a review. Glewwe and Muralidharan (2016) and Murnane and Ganimian (2014) provide some discussion of CCT interventions in comparison to various other education interventions.

[4]See, for example, Baird et al. (2011) for an experimental study that compares CCTs and UCTs on schooling and other outcomes such as early pregnancy.

way. Our study thus has the potential to generate important policy implications on the design of CCTs in developing countries.

Our intervention has a number of distinct features compared to other CCT studies that have looked to improve school attendance. Unlike existing studies, this experiment features (i) nudges through Short Message Service (SMS) and (ii) CCT with loss framing to potentially improve the cost-effectiveness of interventions. These features may be useful, because the former involves no cash transfer and the latter can exploit the widely documented psychological trait of loss aversion—losses loom larger than gains as Kahneman and Tversky (1979) describe it—at no additional program cost. Despite its widespread application, the existing CCT literature provides only limited insights into the features of cost-effective interventions to increase school attendance. This is because most existing studies examine the impact of CCT programs and not the features that would improve their cost-effectiveness. The lack of adequate attention to cost-effectiveness is surprising, particularly given that these programs are typically implemented in developing countries where resources for cash transfers are limited. If the Loss treatment and SMS information can generate the same desired effect at less or no additional cost as compared to the conventional gain framing, policy-makers can adopt loss framing and information nudges to increase secondary school attendance. Our study thus contributes to a small body of literature on efficient design of CCTs, such as de Janvery and Sadoulet (2006), Filmer and Schady (2011), and García and Saavedra (2017), by exploring the following avenues to increase CCT's cost-effectiveness.

First, we study whether simple SMS nudges on school attendance increase the likelihood of children going to school. Since sending SMS is inexpensive and a vast majority of households in the region owns mobile phones, information transmission can be a cost-effective way to bring children to school from the perspective of a policy-maker. Our study shows that this is indeed the case, even though the impact of SMS on attendance is modest compared to the CCT

treatment arms. This indicates that SMS nudges can be an important policy tool in places where resources for policy interventions are limited. We also experimentally explore the relevance of loss framing, which attempts to exploit loss aversion, to CCTs. Since implementing a CCT under a loss framing, instead of the conventional gain framing, can be done virtually at no additional cost, we can potentially make CCTs more impactful for a given amount of transfer. We find that this is possible, even though the additional impact arising from the use of loss framing is small and statistically insignificant.

Second, we vary the amount of transfers to understand the relevance of intensive margin in the treatment, which has largely been unexplored in the literature. The current literature provides little insight into how to do such calibration to have a cost-effective policy. To our knowledge, Filmer and Schady (2011) is the only study that rigorously explores the relevance of intensive margin, but even they have only two levels of transfers while we have three levels. As with other incentive programs, a CCT program with a given transfer amount does not change the behavior of always takers (i.e., households that would send children to school regardless of the presence of the CCT program) and never takers (i.e., households that would not send children to school regardless of the presence of the CCT program). Obviously, never takers may become compliers (i.e., households that would send children to school if and only if some cash transfers are given when the children attend school) when the reward for school attendance is increased. Hence, it is important to calibrate the amount of cash transfers to strike the balance between the increased attendance from compliers and leakage of resources towards always takers in the intensive margin. We provide evidence of diminishing marginal impact of transfer. That is, at a very low level of current transfer, the marginal effect is small. When the current level of transfer is increased, the marginal impact on attendance also goes up. A further increase in the transfer amount leads to smaller increase in attendance, indicating that the marginal impact tends to diminish. Thus, we find that there are diminishing

marginal returns to transfer size.

Finally, we collect daily attendance during our intervention period, as opposed to aggregate attendance rate in a year or school semester. This enables us to investigate the seasonality of the treatment impact across different months or during the lean and harvesting periods. This consideration is important since a sizable fraction of students in our sample belong to agricultural households. We also collect information on social network for each study participant to understand the peer effect in attendance. Taken together, this study offers a new set of insights that could assist policy-makers to design cost-effective interventions to increase school attendance.

We have a number of interesting findings from our analysis. First, morning attendance for students who received a CCT treatment with a loss framing significantly increased by 11.2 percentage points relative to the students in the control group. This impact is higher than that for the conventional CCT treatment under a gain framing, but the difference is statistically insignificant. Second, sending information to parents through SMS also increased attendance by 4.7 percentage points relative to the control arm, which is statistically significant. The SMS treatment arm is found to be more cost-effective than the CCT treatment arms in bringing children to school.

Third, variation in the amount of cash transfer across different phases allows us to test the impact on attendance in the intensive margin. We find that the initial 10 Bangladeshi taka/day (about 0.12 USD/day) is too little to have any perceptible impact on attendance. The subsequent increase to 20 taka/day promotes attendance significantly. However, the marginal impact from a further increase of 20 taka/day to 30 taka/day, though positive and statistically significant, was not as large. Fourth, our analysis reveals that the impact of the CCT treatment with a loss framing is high for agricultural households during the harvest season. This result is particularly apparent in the latter half of 2018, when the transfer amount was increased to 30 taka/day for some participants. Thus,

a moderate amount of cash transfer appears to make a large impact near the harvest season when school attendance drastically declines due to rising income opportunities in the agricultural sector. However, the impact of the same amount of cash transfer is not as large during the lean period, potentially because the opportunity cost of sending children to school may be very small. Fifth, we find evidence of peer effect in attendance across all treatment arms. Interestingly, even when we control for such peer interactions, the point estimates for treatment assignment are similar, indicating that the peer effects are approximately uniform across different treatment arms and the estimated treatment impacts mentioned above are valid net of peer effects. Finally, we find suggestive evidence that the CCT treatment with a loss framing helps older girls in higher grades stay in school and delays incidence of child marriage.

The rest of the paper is organized as follows. In Section 1.2, we review existing studies on loss aversion and information treatment, in particular those with policy applications and discuss the relevance and contribution of our study to this literature. We then provide the details of the design of our field experiment in Section 1.3. Section 1.4 describes the data sources and measurement of school attendance and provides balance checks across different treatment arms at baseline. Section 1.5 discusses the specification of econometric model used in our empirical analysis. Section 1.6 provides our main empirical results on the impact of our treatments on school attendance. Section 1.7 presents the impact on other outcomes such as post-intervention school enrollment, child marriage, child labor, test scores, and spending patterns. Section 1.8 performs a cost-effective analysis for the different treatment arms, and Section 1.9 concludes.

1.2 Relevance and Contributions to the Related Literature

This study explores two possible avenues of increasing the cost-effectiveness of CCTs—loss framing and SMS nudges. As such, in addition to a large body of the CCT literature discussed above, this paper relates to the studies on loss aversion and information treatment, and particularly those with policy applications. In this section, we discuss the relevance and contributions of our intervention to these studies.

The use of loss framing in this study was inspired by the literature on loss aversion, which describes the phenomenon that people tend to react more to losses than to gains of the same amount (Kahneman and Tversky, 1979; Kahneman et al., 1990). Based on an often cited figure, pain from a loss is twice as large as the pleasure from a gain of the same magnitude (Todd and Wolpin, 1991; Tversky and Kahneman, 1992), even though the external validity of this figure is debatable (Chapman et al., 2018; Fehr-Duda and Epper, 2012).

Loss aversion has been increasingly used to explain seemingly irrational behaviors in a wide range of situations, ranging from the supply of cab services in New York City (Camerer et al., 1997; Crawford and Meng, 2011) and measuring productivity of workers in a Chinese high-tech manufacturing facility (Hossain and List, 2012) to credit card use in Israel (Ganzach and Karsahi, 1995) and nutritional choice of American kids (List and Samek, 2015). However, the available evidence on the effectiveness of loss framing relative to gain framing has been mixed, and our result that loss framing has a small but desirable effect adds to this literature. We also offer some explanation as to why the loss framing has only a small effect.

Despite its general appeal, there are only a limited number of applications of loss framing to education policy. For example, Fryer Jr et al. (2012) found moderate impact on mathematics scores of students through loss framed incentives for teachers. Levitt et al. (2016) observed that student performance was

better when rewards were framed in terms of losses than gains, even though the difference was not statistically significant. Since loss framing does not add costs to the conventional gain framing, one could potentially exploit it to increase the cost-effectiveness of a given intervention.

Our intervention also studies the impact of sending attendance information through SMS. Mobile phones have become widespread in the developing and less developed world over the recent years (Howard and Mazaheri, 2009), and this has, on average, led to better educational outcomes (Valk et al., 2010), and employment levels (Klonner and Nolen, 2008). Some studies have exploited this increased access to network coverage and used information transmission as a means to promote attendance at health promotion centres (Chen et al., 2008), and enhance productivity (Fafchamps and Minten, 2012; Abraham, 2006) in the developing world.[5] In our intervention, to disentangle the effect of information provision from loss framing, we also include the SMS treatment arm to identify the impact of conveying attendance information to parents. Since sending SMS is inexpensive, information transmission might be a cost-effective way of getting children to attend school. Hence, this study also contributes to the strand of applied behavioral economics literature that uses the traits of human psychology to design education policies (Jabbar, 2011; Lavecchia et al., 2012; Koch et al., 2015).

Our study is distinct from existing studies in a number of ways. First, contrary to Progresa and most other CCT programs, our conditions for eligibility of cash transfer are linear. This means that cash transfer amount is proportional to the number of school days attended during the intervention period, eliminating the possibility of any threshold effect. As a result, our CCT intervention gives an incentive to *every* household to send children to school on *every* intervention day. In contrast, when there is only one level of transfer per month or school

[5]See Aker and Mbiti (2010) for a comprehensive literature review on the impact of mobile phones on economic development in Africa.

term, the intervention does not give any incentive to those households which have already passed the threshold or which cannot reach the threshold because they have already missed too many days. Our set-up also makes person-day level analysis both straightforward and meaningful. Second, we provide incentives to the household, instead of the teacher or the student. Though there have been studies that have examined the effects of parental involvement on children's educational outcomes in France (Avvisati et al., 2013), we provide direct monetary incentives to the household and conduct the study in a developing country. Third, the timing of the disbursement of cash transfer is delayed where the monetary benefits are distributed to the households at the end of every phase. This allows us to replicate a real-life setting, where daily transfers are impractical. Though SMSes would help reinforce the role of the current transfer amount as the reference amount, one must note that the disbursement at the end of each phase might fail to generate the intended endowment effect for people in the Loss treatment arm. Finally, we collect data on study participants' social network, which enables us to identify peer effect in attendance.

1.3 Design of the Field Experiment

The field experiment was conducted in the district of Gaibandha in northern Bangladesh. Gaibandha is a relatively poor district with 48 percent of the population living below the poverty line in 2016, compared to the national average of 32 percent (World Bank, 2016). It is prone to serious flooding with heavy rainfall from June to August as well as occasional draughts. Given this background, it is not surprising that the Gaibandha district performs poorly in average educational attainment. The primary and secondary education completion rates among adults in the region are 24 percent and 11 percent in 2016, which are below the national averages of 33 percent and 13 percent respectively (World Bank, 2016). Therefore, it is imperative that we understand the school atten-

dance behavior and devise effective policies to bring children to school in places like Gaibandha.

Also, Gaibandha is a predominantly agricultural district, where 71 percent of the working population is in agriculture, a figure well above the national average of 47 percent (World Bank, 2016). Hence, our study area offers an ideal setting to test whether CCT and SMS interventions are effective in bringing children to school from agrarian households across different agricultural cycles. This consideration is important as we may be able to achieve a higher overall attendance by setting the transfer amounts in accordance to the varying opportunity cost of sending children to school.

Timeline of Study

Since a majority of countries in the developing world, including Bangladesh, has achieved universal primary education envisaged in the Millennium Development Goals, education policies have shifted their foci to the enrollment rates at the secondary and higher levels. Against this backdrop, our intervention focuses on secondary school students in grades 6–9 enrolled in one of our three study schools[6] and residing in one of the three catchment unions in Gaibandha.[7]

There were other educational programs that were also implemented in the country during our intervention period, for example, the school-feeding program during 2017-2020 (World Food Programme UN, 2020), and the Female Secondary School Attendance Project that aimed to increase girls' enrollment and retention in secondary schools through stipends and tuition waivers since the early 1990s (Sosale et al., 2019). However, there is no particular reason to believe that the students in our study sample were differentially affected by any

[6] In Bangladesh, secondary education corresponds to grades 6–10.

[7] Unions are the second smallest administrative unit after villages, but before subdistricts, districts, and divisions.

of these interventions.

Our intervention was carried out in academic years 2017 and 2018, where academic years coincide with calendar years. In each of these two academic years, there are two phases of intervention, each of which has a pre-determined number of intervention days—60 days in Phase 1, 2017, and 50 days in all other phases.[8] Thus, not all school days were part of our intervention days. When there were some unexpected school closures, we made adjustments by pushing the end of the phase backward.[9] That is, we change the days that were planned to be non-intervention days before the start of the phase into intervention days. The transfer amount given to households was calculated based only on the attendance of the children during the actual intervention days after adjustments were made.

We recruited 400 students at the start of each of academic years 2017 and 2018. We refer to those who were recruited in 2017 and 2018 as 'old' and 'new' cohorts, respectively. To recruit students, we first obtained a roster of students who were enrolled in the target grades, which were grades 6 and 7 in 2017 and grades 8 and 9 in 2018. We then drew a random sample stratified by the student's gender, school, and grade using the roster, while restricting each household to have a valid mobile phone number and no more than one participating student.[10] All but two study participants from the old cohort were promoted to the next grade in 2018. The timeline of our study and the distribution of our final sample by grade, gender, and cohort, are given in Figure 1.1 and Table A1 of Appendix D respectively.[11]

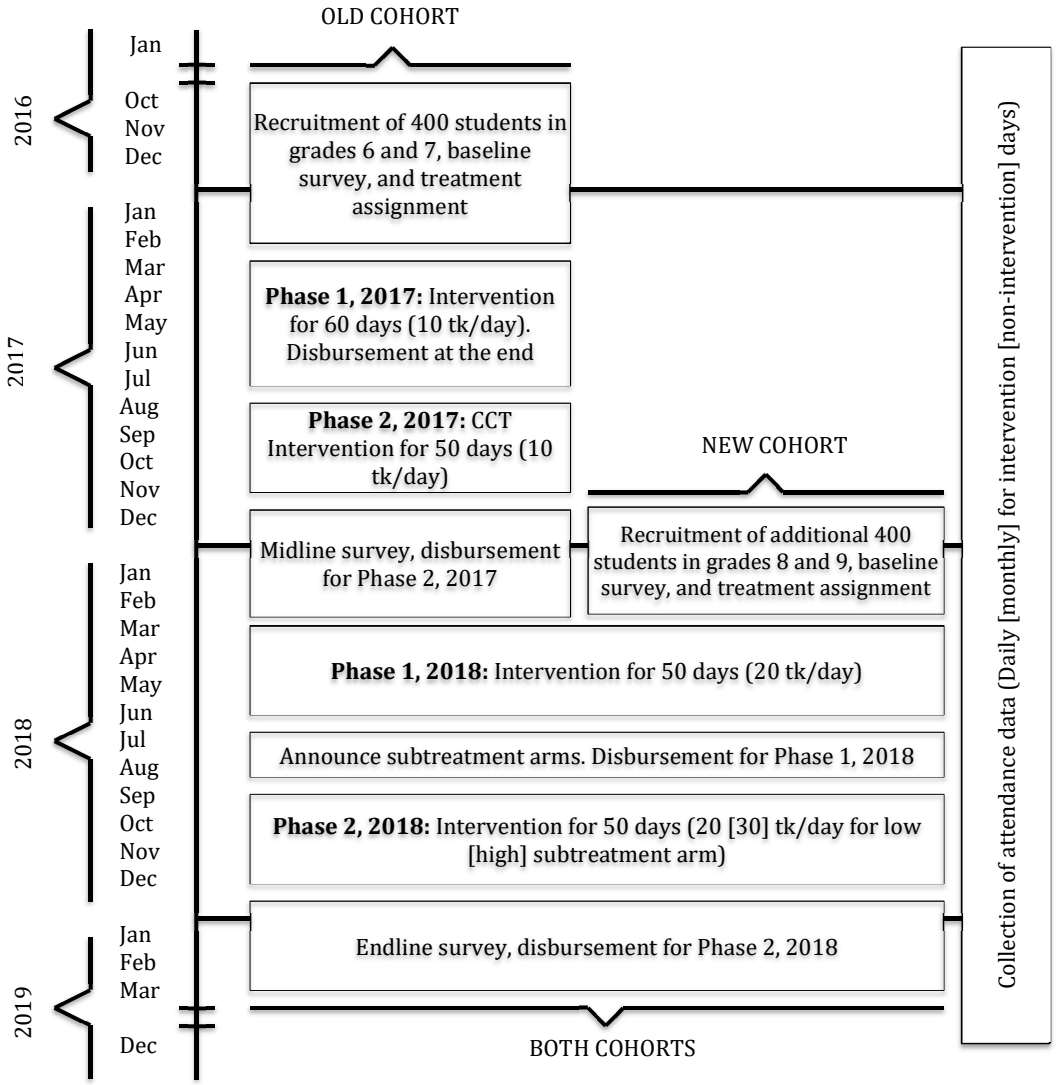
[8]We chose to reduce the number of intervention days after Phase 1, 2017 to be able to cope with the following two unanticipated operational issues: (i) long delay in obtaining the finalized list of enrolled students and (ii) unexpected school closures due to, for example, floods and teacher strikes.

[9]In one of the three study schools, the intervention days for Phase 2 of 2017 had to be cut by five days because of a sustained school closure. For the purpose of cash transfer, these days were treated as attended but they were removed from the analysis.

[10]In the initial roster of all eligible households, 84 percent and 97 percent of the parents in the old and new cohort respectively had a valid phone number.

[11]There were two irregularities in our recruitment process, which happened because of the short timeline (roster only finalized on the first day of school), variation in the spelling of the

Figure 1.1: Timeline of the Study



Note: Daily attendance data are collected during the intervention days. Monthly attendance data are collected from the study schools between 2016 and 2019 outside the intervention days, which include (i) pre-intervention days in 2016 for the old cohort (grade 7 in 2017) and in 2017 for the new cohort (grades 8 or 9 in 2018), (ii) non-intervention days in January, February, June, and December, 2017 and in May, June, July, and December, 2018, and (iii) post-intervention days in 2019. The daily transfer amount in parentheses in each intervention phase is applicable only to the Gain and Loss treatment arms.

Treatment Assignment

In each of the two cohorts, half of the students were assigned to a treatment arm to receive cash transfers of T taka per intervention day attended, where T is fixed for a given household in a given phase and year. Among those who received CCTs, half belonged to the gain framing and the other half to the loss framing. The framing was reinforced by weekly SMS, which provides attendance information and the balance, or the amount of cash that is to be transferred to the household at the end of the intervention phase. Since SMS may have an impact on attendance independent of cash transfers, we created an SMS treatment, to which half of those who did not receive CCTs were assigned. Hence, 100 students from each cohort were randomly assigned to one of the following four treatment arms:

Gain: Households in this treatment arm receive conditional cash transfers with gain framing. That is, households receive T taka for each day the student attends school. The balance starts from zero for this treatment group and the parents receive information on attendance and cash balance through SMS on a weekly basis.

Loss: Households in this treatment arm receive conditional cash transfers with loss framing. That is, households lose T taka for each day the student is absent from school. The balance starts from the maximum possible transfer amount in a given phase. The parents receive information on the child's attendance and cash balance through SMS on a weekly basis.

SMS: Households in this treatment arm receive weekly SMS on the school attendance of their child but no cash transfer.

names, and inaccurate information in the roster, the last of which was corrected subsequently during the baseline survey. First, one student in the old cohort was mistakenly listed in the roster of the new cohort, and was dropped upon realization. Second, there were 10 households with more than one participating child. However, our main findings do not change much if we drop these 10 households.

Control: Households in this treatment arm receive neither cash transfer nor SMS.

The transfer amount T was 10 taka for the two phases in 2017. In Phase 1 of 2018, it was increased to 20 taka. In Phase 2 of 2018, we introduced "High" [H] subtreatment for each of the Gain and Loss treatment arms, which raised the transfer amount to 30 taka per day. In each of Gain and Loss treatment arms, half of the households were randomly allocated to the "High" [H] subtreatment and the remaining half to the "Low" [L] subtreatment, who continued to receive 20 taka per day.

The cash transfers were made at the end of each phase for both the Gain and Loss treatment arms. The timing of disbursement and the amount of transfer are the same for a given attendance record in a given phase. It should be noted that the households in the Loss treatment arm were *not* endowed with cash at the beginning of the phase and that there was a time lag between school attendance and cash transfers. Because transferring cash daily can be administratively too complicated and costly and taking money away from households is difficult, the way we operationalized the loss framing is practical.

The most important difference between the Gain and Loss treatment arms is the way balance changes. That is, the balance starts from zero in the Gain treatment and it goes up as the child attends school. On the other hand, for the Loss treatment arm the balance starts from the maximum amount that can be possibly earned in a given phase, or T taka times the number of intervention days in the phase, and it goes down as the child misses school. To reinforce the effect of framing and make the changes in balance conspicuous to the households, we sent weekly SMS to the Gain and Loss treatment groups. We additionally created an SMS treatment arm to examine the pure effect of providing attendance information as noted earlier. The SMS messages sent to the Gain, Loss, and SMS households are as follows:

Gain: Last week, your child has attended D_a school days and missed D_m school days. You have gained TD_a taka for D_a school days attended. Your current cash transfer balance has increased to B taka.

Loss: Last week, your child has attended D_a school days and missed D_m school days. You have lost TD_m taka for D_m school days missed. Your current cash transfer balance has decreased to B taka.

SMS: Last week, your child has attended D_a school days and missed D_m school days.

In the above messages, T refers to the daily transfer amount in each phase while D_a and D_m refer to the days the child attended and missed school, respectively, over the last week, and B is the balance at the end of the week.

Because disbursement occurs only once at the end of each intervention phase, the gains and losses exist only in the account balance stated in the SMSes sent during the intervention phase. Unfortunately, some issues were discovered in the SMSes sent during the early part of Phase 1, 2018, upon the realization of which we conducted an audit. The inaccuracy of information on attendance, transfer amount, and current balance can undermine the impact of our intervention and would create attenuation bias if the errors are random. The error rates from the audit were found to be very small and not significantly different across the treatment arms. Therefore, our impact estimates are unlikely to be significantly affected by the errors in SMSes and, if anything, they are likely to be slightly attenuated. Further discussion on this issue is provided in Appendix A.

1.4 Data

Data Sources

Our main outcome of interest is school attendance. Because of this and because the amount of cash transfer depends on daily attendance, its accurate measurement is critical for our intervention. Therefore, we collect attendance data for intervention days from three different data sources. The first data source is the morning attendance record, which is the official attendance record maintained by the class teacher before the class begins each morning. This is our primary source of attendance data and the cash transfer amount is computed based on the morning attendance.

Since the students and teachers tend to live near the school, it is plausible that teachers know at least some students' households personally. Hence, they might mark some absent students as present out of sympathy, if they believe that the cash transfer would benefit the students. Also, there is a potential concern for corruption in which students pay the teacher to buy attendance. Therefore, to check if morning attendance is seriously undermined by these issues, we also use a second and third source of attendance record, which are much less likely to suffer from these problems.

The second source of attendance is afternoon attendance, which is collected independently and daily in the afternoon by the class representative of each section engaged by us.[12] Since the afternoon attendance does not relate to cash transfer, there is a minimum concern that it is affected by the issues described above. Further, even if the morning records are completely accurate, the afternoon record is still useful. It is possible that students show up in school in the morning since the cash transfer amount is tied to their morning attendance. Hence, they may leave soon after their morning attendance is taken, if they come

[12] A section is essentially a class in which students study together. In each grade in each school, there are typically up to two sections for lower grades.

to school just to mark attendance. Another reason for not relying solely on the morning attendance is that many students leave school after the lunch break and hence morning attendance captures partial attendance of the entire school day (Star, 2015; Tuhin, 2018). Clearly, our intervention would be of no practical purpose if any of these occurs. Hence, afternoon attendance allows us to see whether each student continued schooling after tiffin or the mid-day lunch break.

The third source of attendance data comes from unannounced random visits to schools. There were about eight visits a year to cross-validate our morning and afternoon attendance records. Since the visits were made by field officers who have no personal relationship with the students, they are least susceptible to arbitrary manipulation.

In addition to the above-mentioned daily attendance data, we also collected official monthly attendance records, which cover years between 2016 and 2019.[13] To understand the pre-intervention attendance trends across different treatment arms, we collected aggregate monthly attendance records from study schools in the pre-intervention year (2016 for the old cohort, and 2017 for the new cohort). Since a large fraction of students from the old cohort were in grade 6 in 2017 and thus were in a primary school in 2016, we do not have their pre-intervention attendance records.

We are also interested in seeing whether the effects of our intervention are fleeting or persistent. Thus, we collect monthly attendance data for the year 2019. However, because students may transfer to a different school or drop out of the school, we do not have information on the attendance records for 210 students in 2019 (92 students from the old cohort, and 118 students from the new cohort). We also collected monthly attendance data for the non-intervention school days in the years 2017 (old cohort only) and 2018 (both cohorts).

[13]Monthly data, instead of daily data, were collected because of the limited data availability in 2016 and limited budget for data collection.

In addition to the attendance records, we also gather household-level and individual-level data through surveys. We administered a baseline survey to the households of students participating in the study before the treatment assignment was announced. After the intervention, an endline survey was administered to them except for the 16 households that could not be reached possibly because of migration. For the old cohort, we additionally conducted a midline survey between Phase 2, 2017 and Phase 1, 2018 (see Figure 1.1). The surveys collected information on a host of variables, such as consumption and assets of the household and age, sex, education, and employment of each household member.

We also carried out disbursement surveys for the Gain and Loss treatment arms at the end of every phase during the household visits for cash disbursement. The disbursement surveys were integrated into midline survey in Phase 2, 2017 and endline survey in Phase 2, 2018. These surveys asked households how they plan to utilize the cash received from the study for different purposes such as education and purchase of luxury goods. Additionally, in the midline and endline surveys, the households were asked to provide retrospective information on how the cash was utilized on various household expenditures. Finally, the disbursement survey also contained questions on the understanding of the CCT intervention, the recollection of the amount that they were supposed to receive, and whether they kept a record of the SMS that was sent to them at the end of every week. All questions were asked before the money was actually disbursed.

Summary Statistics and Balance Checks

As mentioned earlier, the cash transfer given to a household at the end of each phase is based on the official morning attendance record. However, due to concerns arising from possible misreporting of morning attendance data or students leaving school after morning attendance has been taken, we additionally have

data from afternoon attendance and random visits. Our raw data suggest that these concerns are unlikely to be important and that the morning attendance record is a reliable measure of school attendance. As shown in Table 1.1, there is a strong positive correlation between morning and afternoon attendance records from over 123 thousand person-day records. For nearly 90 percent of the valid person-day records, morning attendance matches afternoon attendance. The off-diagonal elements in Table 1.1 indicate that the odds of students leaving school early before afternoon attendance are higher than those of students coming later after morning attendance.

Moreover, the attendance records from unannounced random visits also have a high correlation between morning and afternoon attendance. Based on the 8,876 person-day observations with all the three attendance records, the correlation is the highest at 0.87 between morning and random visit records. This is to be expected because the random visit records are likely to capture the attendance of some early leavers (Table 1.1). The correlation between afternoon and random visit records is 0.79, which is higher than the correlation of 0.76 between morning and afternoon records. Again, this ranking is to be expected because random visit records are likely to capture attendance of some latecomers.

Besides attendance measurement, the random assignment of students to the four different treatment arms is also critical. Since the random assignment was made by the research team, there was no concern for arbitrary manipulation. Nonetheless, the assignment can be unbalanced by chance. Therefore, we performed a balance check for 16 household characteristics including parental education, household size, possession of assets, children's height and weight, and baseline test scores. This exercise was done separately for the old and new cohorts. No significant difference across the four treatment arms was found in any of the 16 variables for the old cohort by a pairwise t-test of equality of means. For the new cohort, the proportion of households with an agricultural land and

Table 1.1: Morning and Afternoon Attendance on Valid School Days

	Afternoon Present	Afternoon Absent	Total
Morning Present	52.10	7.35	59.45
Morning Absent	3.07	37.47	40.54
Total	55.17	44.82	100.0

Note: Based on 123,500 person-day observations with 799 unique individuals in the study and 239 unique calendar days. The correlation coefficient for the morning and afternoon attendance from these observations is 0.79. The number of unique calendar days is larger than the total number of intervention days in Figure 1.1 because of the differences in school calendars and unexpected school closures in some schools.

that with a television or radio at home for the SMS treatment arm was significantly larger than that for the Gain treatment arm. The joint test of equality of means for the old and new cohort reported in Tables A2 and A3 in Appendix D respectively also show that there is no significant difference in observable characteristics across the four treatment arms, except for the ownership of agricultural land and possession of television/radio for the new cohort.

1.5 Empirical Specification

Our baseline specification is:

$$\mathrm{Y_{it}} = \alpha + \beta_1 \mathrm{Gain}_i + \beta_2 \mathrm{Loss}_i + \beta_3 \mathrm{SMS}_i + \gamma X_i + \theta Z_i + \phi D_t + \varepsilon_{it}, \qquad (1.1)$$

where $\mathrm{Y_{it}}$ is an attendance outcome indicator that takes a value of one if individual i is present in school in day t, and zero otherwise. As attendance outcome indicators, we analyze morning attendance, afternoon attendance, attendance at

the time of random visits, and "morning & afternoon" attendance, the last of which requires that the individual is present both in the morning and afternoon. Gain_i, Loss_i, and SMS_i are indicator variables that take a value of one if the individual i belongs to the Gain, Loss, and SMS treatment groups, respectively, and zero otherwise. The main coefficients of interest are β_1, β_2 and β_3.

Since the ownership of agricultural land and possession of television/radio at the baseline were not balanced across treatment arms, we additionally include these variables in X_i in equation (1.1). We also incorporate the fixed effects terms at the levels of cohort-school-grade combination (Z_i) and calendar date (D_t) to control for any unobserved heterogeneity at these levels. The errors term ε_{it} is clustered at the individual level.

Besides the above specification, we also consider a difference-in-differences (DiD) specification with individual-level fixed effects using monthly aggregate data before the start of intervention and during intervention (including monthly attendance for non-intervention days). The individual-level fixed-effects specification takes the following form:

$$\begin{aligned} \text{Y}_{it} &= \alpha + \beta_1 \text{Gain}_i \times \text{TreatmentYear}_{it} + \beta_2 \text{Loss}_i \times \text{TreatmentYear}_{it} \\ &\quad + \beta_3 \text{SMS}_i \times \text{TreatmentYear}_{it} + \phi_i + \gamma_t + \varepsilon_{it} \end{aligned} \tag{1.2}$$

where the reference category is monthly attendance for the year 2016 [2017] for the old [new] cohort. Note that the old cohort students include only those who were in grade 7 as of 2017 because pre-intervention attendance records are unavailable for the old-cohort students who were in grade 6 as of 2017. The treatment year indicator $\text{TreatmentYear}_{it}$ takes a value of one in both 2017 and 2018 for the old cohort and only in 2018 for the new cohort, and a value of zero otherwise. We denote the individual- and year-month-specific fixed effects by ϕ_i and γ_t, respectively. The error term ε_{it} is clustered at the individual level. The specification above has the advantage of being able to control for all time-

invariant individual characteristics that affect attendance. Because the proportion of intervention days among all school days varies across different months, we also consider a specification in which the interaction terms in eq. (1.2) further multiplied by the fraction of intervention days among all school days in the given calendar month are included in the regression.

1.6 Results

Main Findings

As reported in column (1) of Table 1.2, the Gain treatment increases morning attendance in school by about 11 percentage points, based on the regression estimates in eq. (1.1). The impact of the Loss treatment is slightly higher, but the difference between the Gain and Loss treatment is not statistically significant. The SMS treatment arm, on the other hand, increased attendance by 4.7 percentage points. The estimates are similar even when alternative measures of attendance such as afternoon attendance (column (2)), morning & afternoon attendance (column (3)), and attendance upon random visit (column (4)) are used. This is to be expected since the morning attendance records taken by the class teacher closely match with other attendance records.

The similarity of the results across columns is nevertheless reassuring. If students came to school only to mark attendance for the cash transfer and left immediately after the morning attendance was taken, the CCT would have been of no practical value for education. However, Table 1.2 does not show any evidence with such a possibility since the estimated impacts of the CCT treatment arms (i.e., Gain and Loss treatment arms) on afternoon attendance in such a scenario would have been weaker than those on morning attendance. To further strengthen our case, we also use afternoon attendance as the outcome variable for the subsample of person-day records where the child was present in the morning. As shown in Table A4 in Appendix D, the Gain, Loss, and SMS

treatments all had positive and significant effects on afternoon attendance conditional on morning attendance. While we included the unbalanced covariates and cohort-school-grade and day fixed effects in Table 1.2 to remove confounding from these variables and increase the precision of the estimates, we also consider the pure experimental design by removing X_i and the fixed effects from eq. (1.1) and adjusting for multiple hypothesis testing. Doing this does not change our results much qualitatively or quantitatively except that the statistical significance of SMS treatment is weakened as shown in Table A5 in Appendix D.

Robustness Checks

Our results may be potentially driven by differential attrition rates across different treatment arms. Hence, we re-estimate the impact of treatment on attendance by dropping those discontinued students who left the study at any point during the two year period, which include students who dropped out of school or transferred to a different school.[14] As reported in Tables A6 and A7 in Appendix D, the point estimates become higher for all the treatment arms—Gain, Loss, and SMS, and no significant difference exists in the attrition rates across the four treatment arms respectively. Using an alternative definition of attrition, where an individual is identified as missing if the endline survey was not administered to the individual, does not change the results qualitatively or quantitatively.[15]

The main findings we presented above also remain unchanged when we use various alternative specifications. We check the pre-intervention attendance data to see if our point estimates are driven by differences in attendance rates at the baseline. Table A8 in Appendix D shows that the attendance rates were balanced across all treatment arms in the pre-intervention period. It should be reiterated

[14]There were 79 such discontinued students—44 and 35 from the old and new cohorts, respectively. Discontinuation is likely to be an inaccurate measure because it is generally difficult to distinguish between long-term absence and dropout. Nevertheless, there is also no significant difference in the attrition in the endline survey across different treatment arms.

[15]Using the alternative definition of attrition based on administration of endline survey, there were 16 missing students—8 from the old cohort and 8 from the new cohort.

Table 1.2: Treatment Effect for All Students: Baseline Specification

Dependent variable	Morning (1)	Afternoon (2)	Morning & Afternoon (3)	Random Visit (4)
Gain	0.107***	0.120***	0.123***	0.092***
	(0.025)	(0.026)	(0.025)	(0.026)
Loss	0.112***	0.129***	0.130***	0.128***
	(0.024)	(0.025)	(0.024)	(0.025)
SMS	0.047**	0.055**	0.056**	0.069***
	(0.024)	(0.024)	(0.024)	(0.026)
P(Gain=Loss)	0.859	0.749	0.785	0.159
P(Gain=SMS)	0.027	0.020	0.015	0.380
P(Loss=SMS)	0.014	0.006	0.005	0.020
Observations	123,500	123,500	123,500	8,869
R-squared	0.064	0.078	0.076	0.041
Control mean	0.534	0.481	0.449	0.605

Note: “Morning" takes a value of 1 if the child was present in school in the morning, and 0 otherwise. “Afternoon" takes a value of 1 if the child was present in school in the afternoon, and 0 otherwise. “Morning and Afternoon" takes a value of 1 if the child was marked present in both the morning and afternoon attendance record, and 0 otherwise. “Random visit" takes a value of 1 if the child was present in school on the day of the random visit, and 0 otherwise. The Control treatment arm is the reference category in all regressions. The *p*-values for the test of equality of means between two different treatment arms are given in the middle panel. The above specifications control for cohort-school-grade and day fixed effects. They also control for unbalanced covariates at baseline - ownership of agricultural land and radio/television. Standard errors are clustered at the individual level are given in parentheses. ***, **, and * denote statistical significance at 1, 5, and 10 percent levels, respectively.

that the sample used for this analysis comprises of only grade 7 students in 2017 (from the old cohort), and grade 8 and grade 9 students in 2018 (from the new cohort), since the grade 6 students in 2017 were in a primary school in the preceding year.

Table 1.3 performs a DiD analysis employing monthly attendance data for old-cohort students who were in grade 7 in 2017 and all new-cohort students. The odd-numbered columns use standard DiD specifications while the even-numbered columns control for the intensity of treatment within a month using the fraction of intervention days in the total number of valid school days. Columns (1) and (2) use data between 2016 and 2018, whereas columns (3) and (4) additionally use data for 2019 and estimate the impact of treatment assignment in the post-intervention period to conduct a test of persistence of treatment. This test is of interest, because our treatments may let the households realize the benefits of attending school and change their behavior even after the intervention period is over. If this is the case, our treatments can generate a long-term impact.

Table 1.3 shows that the addition of 2019 in the analysis does not change the estimated impacts of our treatments much during the intervention years. Further, as column (3) of Table 1.3 shows, the impacts of the Loss and SMS treatments appear to be persistent. However, the results are only marginally significant. Further, once we control for the treatment intensity, the treatment effects are no longer significant. Hence, we have limited evidence of persistence in school attendance beyond the intervention period.

Finally, we cluster errors at the grade, school, school-grade, and section level to account for the possibility of spillovers, and our results are robust to these alternative specifications. (Appendix D Table A9).

Table 1.3: Individual Fixed Effects Specification

	2016–2018		2016–2019	
Dependent variable: Monthly attendance rate	(1)	(2)	(3)	(4)
Gain × TreatmentYear	0.106***		0.110***	
	(0.029)		(0.027)	
Loss × TreatmentYear	0.124***		0.131***	
	(0.029)		(0.028)	
SMS × TreatmentYear	0.027		0.030	
	(0.026)		(0.025)	
Gain × TreatmentYear × TrIntensity		0.128***		0.134***
		(0.023)		(0.023)
Loss × TreatmentYear × TrIntensity		0.134***		0.141***
		(0.024)		(0.023)
SMS × TreatmentYear × TrIntensity		0.005		0.007
		(0.022)		(0.022)
Gain × 2019			0.048	0.026
			(0.031)	(0.025)
Loss × 2019			0.058*	0.024
			(0.034)	(0.026)
SMS × 2019			0.053*	0.035
			(0.031)	(0.025)
Observations	14,178	14,178	20,304	20,304
R-squared	0.490	0.493	0.456	0.458

Note: Columns (1) and (3) are based on standard DiD specifications. Columns (2) and (4) control for the intensity of treatment within a month using the fraction of intervention days. The outcome variable in both the specifications is monthly attendance rate. Monthly attendance rates for each student are calculated by dividing the total number of days present by the valid number of school days in a given month. The Control treatment arm is the reference category in all regressions. The above specifications control for household and year-month fixed effects. TreatmentYear is an indicator function that takes a value of 1 if the individual belongs to the old cohort and the attendance data is for the year 2017/2018, or the individual belongs to the new cohort and the attendance data is for the year 2018. TrIntensity denotes the fraction of intervention days in the number of school days in a given month. Standard errors clustered at the individual level are given in parentheses. ***, **, and * denote statistical significance at 1, 5, and 10 percent levels, respectively.

Heterogeneity Analysis

Restricting all the coefficient estimates to be identical across the entire sample masks various types of impact heterogeneity that may exist. For example, the baseline specification in eq (1.1) does not capture the variation in treatment effects at the intensive margin. Also, the treatment effects could significantly vary across different months of the year, and they could also differ based on pre-intervention attendance, gender of the child, education level of parents, distance from school, and occupation and economic status of the household. The impact estimates could also be different based on how well the households were able to recollect the transfer amount and whether they kept records of weekly SMS. We therefore explore the impact heterogeneity in these dimensions.

We first analyze the effect of treatment assignment at the intensive margin through a non-experimental design by allowing the effect of Loss and Gain treatments to depend on the quantity of transfer. Table 1.4 shows that the initial 10 taka/day had no significant impact on attendance. However, the additional 10 taka/day transfer had significantly improved attendance. The effects were further magnified when the transfer amount was increased to 30 taka/day, but the incremental gain from 20 taka/day to 30 taka/day in attendance was smaller than the incremental gain from 10 taka/day to 20 taka/day. This suggests that the marginal impact of transfer is diminishing. The same conclusion is reached when we alternatively use a model that is quadratic in the transfer amount (See Appendix C).

We also observe consistent results when we perform heterogeneity analysis by phase. Among all phases, the attendance impact of the CCT treatments is the highest in phase 2 of 2018, when the daily transfer was raised to 30 taka/day for the “High" subtreatment households in each CCT treatment arm (Table A10 in Appendix D). Further, even though the difference is statistically insignificant, the attendance impact of CCT treatments is higher for the households in the

“High" [H] subtreatment than that for the “Low" [L] subtreatment in phase 2 of 2018 (Table A11 in Appendix D). Taken together, our results indicate that the intensive margin of cash transfer matters.

Second, the seasonality of the treatment effect is of interest. Figure 1.2 shows the attendance rates across different treatment arms for the years 2017 and 2018. It suggests the presence of seasonality in attendance and treatment effects. In particular, the CCT treatment arms have a greater impact on attendance during the planting and harvesting periods for two of the major crops, *aus* and *aman* in the region. The planting and harvesting times are, respectively, May–June and July-August for *aus* and August–September and November–December for *aman*.

The seasonality effect is particularly interesting when we perform a heterogeneity analysis by occupation. Figure 1.3 shows the differential impact between agricultural and non-agricultural households for each treatment arm during the intervention months of 2017 and 2018, respectively.[16] The point estimates for 2017 are small in absolute value and noisy because both the transfer amount and sample size are small. However, the corresponding estimates for 2018 exhibit a clearer pattern. The difference in attendance rate between agricultural and non-agricultural households for the Loss treatment arm is positive and increases during the months of August and September, which are also the harvesting time for *aus* and planting time for *aman* respectively. The month of August also marked the beginning of the second phase of 2018 when the “High" [H] and “Low" [L] subtreatment arms were introduced. The greater impact of the Loss treatment on agricultural households relative to non-agricultural households can be attributed to at least two possible reasons. First, the increased transfer amount for the “High" [H] subtreatment perhaps enabled agricultural households to cover the opportunity cost of sending the child to school during

[16]Households where at least one member is self-employed (primary or secondary occupation) in agriculture, forestry or aquaculture are defined as agricultural households.

Table 1.4: Treatment Effect by Amount: Non-linear Specification

Dependent variable	Morning (1)	Afternoon (2)	Morning & Afternoon (3)	Random Visit (4)
Gain (10tk)	-0.014	-0.011	-0.007	-0.023
	(0.033)	(0.035)	(0.035)	(0.035)
Gain (20tk)	0.090***	0.092***	0.093***	0.052*
	0.030	0.030	0.030	0.030
Gain (30tk)	0.133***	0.150***	0.151***	0.057
	0.039	0.039	0.039	0.045
Loss (10tk)	-0.009	0.004	0.000	0.012
	(0.031)	(0.033)	(0.033)	(0.033)
Loss (20tk)	0.089***	0.093***	0.096***	0.075**
	0.030	0.030	0.030	0.029
Loss (30tk)	0.154***	0.170***	0.172***	0.142***
	0.038	0.038	0.038	0.042
SMS	0.048**	0.056**	0.056**	0.069***
	0.024	0.024	0.024	0.026
Observations	123,500	123,500	123,500	8,869
R-squared	0.067	0.082	0.080	0.043
Control mean	0.534	0.481	0.449	0.605

Note: The above estimates are from a non-linear specification. “Morning" takes a value of 1 if the child was present in school in the morning, and 0 otherwise. “Afternoon" takes a value of 1 if the child was present in school in the afternoon, and 0 otherwise. “Morning and Afternoon" takes a value of 1 if the child was marked present in both the morning and afternoon attendance record, and 0 otherwise. “Random visit" takes a value of 1 if the child was present in school on the day of the random visit, and 0 otherwise. The Control treatment arm is the reference category in all regressions. The above specifications control for cohort-school-grade and day fixed effects. They also control for unbalanced covariates at baseline - ownership of agricultural land and radio/television. Standard errors clustered at the individual level are given in parentheses. ***, **, and * denote statistical significance at 1, 5, and 10 percent levels, respectively.

the harvest season. Second, there may be interactions between loss aversion and transfer amount. That is, the difference between Gain and Loss treatment arms would be small when the transfer amount is small. However, when the transfer amount is large, the effect of loss aversion may become more obvious.

Besides whether the household is agricultural, our CCT treatments would generally be more impactful for households that are at the margin of sending the child to school or not. In this paper, we examine several dimensions that may be related to whether the household is close to the margin. First, cash transfers might be able to incentivize parents in the Gain and Loss treatment arm, whose pre-intervention attendance rates were low, to send their kids to school. As shown in Appendix D Table A12, for the Gain treatment group, the treatment effects are higher for students whose pre-intervention rate was above median, while for the Loss treatment group, the treatment effects are marginally higher for students whose pre-intervention attendance rate was below median. Though these differences are not statistically significant, loss framing appears to be more effective for students whose baseline attendance is low. Second, we study the impact heterogeneity by gender. If the parents in our sample value the education of the girl child less, the impact of our treatment assignment might differ considerably between boys and girls. Though the control mean for female students in our sample is higher than their male counterparts, the point estimates for female students are consistently larger than male students across all treatment arms (Appendix D Table A13). However, none of these differences are statistically significant as shown in the middle panel. Third, education is a human capital that is often intergenerational with less educated parents often having offsprings who are poorly educated, thus giving rise to a vicious cycle of poverty (Oreopoulos et al., 2006; Coneus and Sprietsma, 2009; De Haan, 2011). We look at treatment heterogeneity by education levels of both the parents of the study participants (Appendix D Table A14). While there is no significant difference in impact estimates across education levels of parents for each of the

treatment arms, the point estimates for the Gain treatment arm are increasing in magnitude as the education level of the father increases. Though there is no clear pattern for the education level of the mother, children in households where the father is more educated (completed secondary or tertiary education) are more likely to attend school. Fourth, we analyze the heterogenous treatment effect by the distance from school. Though the difference in the treatment impacts between households whose distance from school is below and above the median (7.84 kilometers) is statistically insignificant for each treatment arm, all treatments are observed to have a greater impact on attendance for the above-median households (Appendix D Table A15). Fifth, we also study the differential impact of the intervention across different quartiles of predicted consumption per capita, which serves as a proxy for household economic status (See Appendix B for a description of this measure). While the impact of the Loss treatment arm is stable across different quartiles, the point estimates for the Gain treatment are the highest for the richest quartile, even though there is no significant difference in the effect of each treatment across the four quartiles according to an F-test for equality of means (Appendix D Table A16). Thus, while there are some indications of potential presence of impact heterogeneity, our results are not driven by the impact heterogeneity due to pre-intervention attendance rates, gender of the child, education level of household head, distance to school or consumption level.

Finally, the success of such CCT interventions is likely to depend on the understanding of the participants. Before the disbursement of cash at the end of each intervention phase, CCT households were asked in the disbursement survey to state the final balance to be transferred to them and with due permission, their phones were checked to see whether they had retained the weekly SMS. About four-fifth of the respondents claimed that they remember the actual cash balance, and nearly all of them stated the correct balance. Around 90 percent of the respondents said that they had not deleted the SMS on their phones prior to

disbursement. We use these pieces of information to see whether remembering the CCT transfer amount and retaining the SMS are correlated with attendance. We find that both of them are positively correlated with morning attendance. In particular, remembering the CCT transfer amount is positively and statistically significantly associated with morning attendance, even after controlling for the household fixed-effects (Appendix D Table A17). While we cannot make a causal inference here, our results indeed suggest that understanding of the intervention is important.

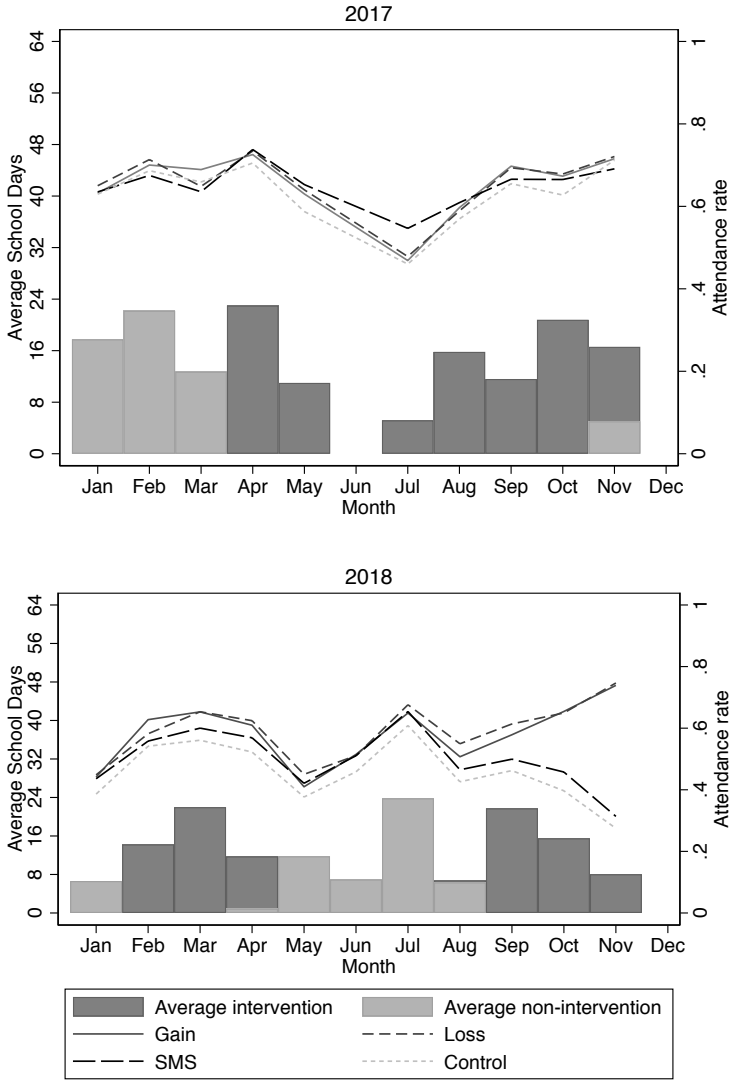
Peer Effect in Attendance

We have not accounted for the possibility of spillover in our analysis so far. However, the anecdotal evidence gathered through informal interactions with some study participants indicates that students tend to make a collective—rather than individual—decision with their friends to attend or skip school. Therefore, it is important to account for potential presence of significant spillover effect arising from peer interactions.

If the peer effect on attendance is positive and unilateral from the treatment groups to the control group, the estimates presented so far would understate the true impact of our interventions. On the other hand, if the peer effect is similar across all treatment arms, our estimates would reflect the true treatment impact net of spillovers. The latter possibility is plausible since treatment assignment is random and thus the impact of our intervention on peers should be similar across all treatment arms.

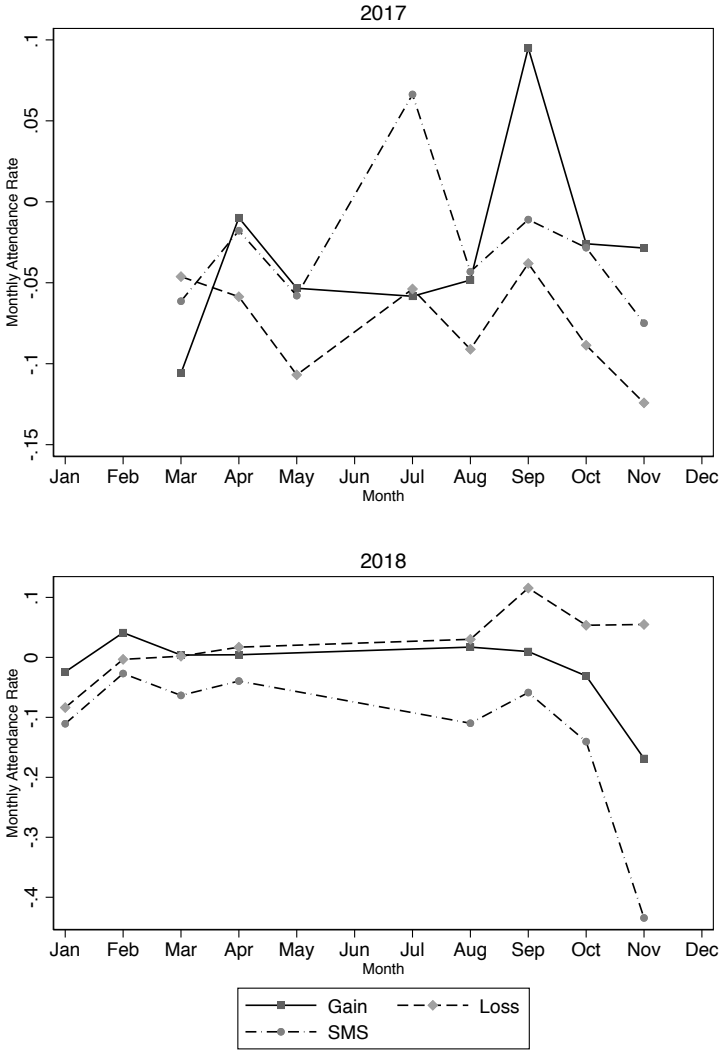
To understand the peer effects, we collected social network data for each study participant. Specifically, we asked each study participant to report the names of his/her five best friends from the same school and grade in each of the survey rounds. Thus, the social network data would have friends who were in the same school and grade but might not necessarily be part of our intervention.

Figure 1.2: Monthly Attendance Rates in 2017 (top) and 2018 (bottom)



Note: In each figure above, the number of intervention days (black) and non-intervention days (grey) averaged over all students are given in the bar chart (left axis) and the average monthly morning attendance rates for the different treatment arms using aggregate monthly data, including both intervention and non-intervention days, are given in line graphs (right axis). The non-intervention months in the year 2017 were January, February, June, and December, and in 2018 they were May, June, July, and December. There was no school day in the month of June in 2017. December is omitted from the graph since students go to school only for the final examination.

Figure 1.3: Treatment Heterogeneity by Occupation for 2017 (top) and 2018 (bottom)



Note: In each figure above, the differences in treatment impacts between agricultural and non-agricultural households are given. To this end, monthly attendance rates, which are based on both intervention and non-intervention days, are regressed on the treatment assignment indicators separately for agricultural and non-agricultural households and the differences in point estimates between agricultural and non-agricultural households for each treatment arm (relative to the control arm) are plotted. The non-intervention months in the year 2017 were January, February, June, and December, and in 2018 they were May, June, July, and December. There was no school day in the month of June in 2017. December is omitted from the graph since students go to school only for the final examination.

All survey respondents gave exactly five names.[17]

The names of the reported friends were matched to those of the study participants within each school-grade combination by engaging research assistants who are proficient in Bengali. The match was not perfect because of name variations, though we have no reason to believe that the errors in matching differ across different treatment arms. After matching was completed, we computed the proportion of friends who were there in each treatment arm. We denote the proportion of the five friends who are in the Gain treatment arm at the baseline by GainProp and use a similar notation for other treatment arms. For example, suppose that the names of four out of five best friends for a given study participant were matched within the same school-grade combination and assume that he has two, one, one, and zero friends from the Gain, Loss, SMS, and Control treatment arms, respectively. Then, we have: GainProp $= 0.4$, LossProp $= 0.2$, SMSProp $= 0.2$, and ControlProp $= 0.00$, respectively. Note that the sum of these proportions does not necessarily add up to unity, because there may be some friends who could not be matched due to name variations or because they were not part of our sample.

Using these data, we test the hypothesis that having a higher proportion of friends in the CCT or SMS treatment arms generates a positive spillover effect on attendance. Specifically, we adopt the following specification using the data for both cohorts.

$$\begin{aligned} \mathrm{Y_{it}} &= \alpha_0 + \alpha_1 \mathrm{Gain}_i + \alpha_2 \mathrm{Loss}_i + \alpha_3 \mathrm{SMS}_i + \alpha_4 \mathrm{GainProp}_i \\ &\quad + \alpha_5 \mathrm{LossProp}_i + \alpha_6 \mathrm{SMSProp}_i + \alpha_7 \mathrm{ControlProp}_i + \varepsilon_{it} \end{aligned} \tag{1.3}$$

As reported in Table 1.5, we find evidence of significant peer effect. If the proportion of friends in the Gain treatment group goes up by one unit, atten-

[17] We chose to collect data in this way instead of attempting to collect complete social network data because our budget was limited and because the peer effect is likely to come primarily from best friends.

dance of the individual increases by 11.5 percentage points (column (2) of Table 1.5). There is a significant peer effect of having friends in the Loss treatment and SMS treatment arm as well, and the estimates are significant at the one percent level. However, the treatment effects are similar to the baseline specification (column (1) of Table 1.2).

While these point estimates may appear large, the average spillover effects implied by these figures are of plausible magnitude. Using the point estimates in column (2) of Table 1.2, the spillover effect evaluated at the sample average (i.e., use sample averages of GainProp, LossProp, SMSProp, and ControlProp) is 1.6 percentage points relative to the case when all friends are non-participants. Given that about 53 percent of students are study participants in the participating sections based on our roster, the overall impact on the section-level attendance can be estimated at $5.1 (= 1.6 + ((10.7 + 11.2 + 4.7) \times 0.53/4))$ percentage points using the estimates in Column (1) of Table 1.2. This holds true under the assumption that the spillover effects for non-participating and participating students in the participating sections (i.e., sections with students participating in this study) are the same and that there is no direct program effect for the control and non-participating students.

To verify the validity of this estimate, we compare this figure to the results of a section-level analysis using monthly attendance data from years 2016 to 2018 (Table A18 in Appendix D), which include both participating and non-participating sections. Specifically, we regress the section-level monthly attendance rate on the indicator variable for the intervention months for participating sections weighted by the number of valid school days. The point estimate of the coefficient on the intervention month is positive and statistically significant in the specification without the fixed effects for each of calendar month, calendar year, grade, and school. Further, the point estimate is close to and statistically indistinguishable from 5.1 percentage points regardless of the inclusion of fixed effects. Notice that the point estimates from the section-level

data would underestimate the overall impact of our intervention to the extent that there are spillover effects from participating sections to non-participating sections. Subject to this caveat, these crude calculations suggest that our intervention increased the attendance rate at the section level by around 5 percentage points out of which about a third could be attributed to the spillover effects.

1.7 Impact of the Intervention on Other Outcomes

Our rich dataset enables us to study the impact of the intervention on various other outcomes of interest. In this paper, we focus on the following outcomes that may be closely related to attendance: school enrollment, child labor, child marriage, test scores, and spending patterns. Though the impact of our intervention on attendance was short-lived and did not last beyond the intervention period, it can potentially increase the enrollment rates in school. We analyze the enrollment rates in 2019 to understand whether our intervention helped keep students in school for longer. Further, two important reasons why children may drop out of school are child labor and child marriage. These two outcomes may also be affected by our CCT intervention, because CCT can lower the opportunity cost of attending school, particularly for boys belonging to agricultural households. Similarly, the incidence of child marriage for girls, particularly those in higher grades, may be affected, because the lower opportunity cost of education would reduce the need for households to marry off girls early (Field and Ambrus, 2008; Amin et al., 2016). For boys, incidence of child marriage is low; no boy was married at the baseline and only one was married at the endline. Hence, we focus on child marriage for girls.

Test score is another important outcome to look at both from policy and research perspectives, because increased school attendance may or may not lead to better learning outcomes. There might be serious supply side constraints such as high student-teacher ratio in schools or lack of requisite home learning aids

Table 1.5: Impact of Social Network on Attendance

Dependent variable	Morning Attendance		Afternoon Attendance	
	(1)	(2)	(3)	(4)
Gain	0.101***	0.106***	0.116***	0.120***
	(0.004)	(0.004)	(0.004)	(0.004)
Loss	0.105***	0.109***	0.123***	0.126***
	(0.004)	(0.004)	(0.004)	(0.004)
SMS	0.034***	0.044***	0.042***	0.052***
	(0.004)	(0.004)	(0.004)	(0.004)
GainProp	0.119***	0.115***	0.182***	0.150***
	(0.011)	(0.011)	(0.011)	(0.011)
LossProp	0.076***	0.051***	0.061***	0.034***
	(0.011)	(0.011)	(0.011)	(0.011)
SMSProp	0.101***	0.099***	0.145***	0.128***
	(0.012)	(0.012)	(0.012)	(0.012)
ControlProp	-0.042***	-0.084**	-0.063***	-0.104***
	(0.012)	(0.012)	(0.012)	(0.012)
P(Gain = Loss)	0.324	0.397	0.098	0.108
P(Gain = SMS)	0.000	0.000	0.000	0.000
P(Loss = SMS)	0.000	0.000	0.000	0.000
Observations	123,500	123,500	123,500	123,500
R-squared	0.010	0.060	0.015	0.072
Cohort-School-Grade FE	No	Yes	No	Yes
Day FE	No	Yes	No	Yes

Note: “Morning Attendance" takes a value of 1 if the child was present in school according to morning attendance on a given day, and 0 otherwise. “Afternoon Attendance" takes a value of 1 if the child was present in school according to afternoon attendance on a given day, and 0 otherwise. The Control treatment arm is the reference category in all regressions. GainProp denotes proportion of friends in the Gain treatment arm at the baseline. LossProp, SMSProp, and ControlProp are similarly defined for the Loss, SMS, and Control groups. The p-values for the test of equality of means between two different treatment arms are given in the middle panel. Standard errors clustered at the individual level are given in parentheses. ***, **, and * denote statistical significance at 1, 5, and 10 percent levels, respectively.

in the form of private tutoring and sibling or parental support especially for first generation learners, which our study would not have addressed. Finally, it is important to understand how the households utilize the extra cash received for the child's attendance in school. If the households spend the additional money on unnecessary luxury items or sin goods such as alcohol and cigarettes, the intervention will not provide any additional benefits to the child beyond school attendance. Thus, it is important to examine whether the cash provided by the CCT intervention benefited the child.

Enrollment Rate

Dropout rates generally tend to increase as students progress to higher grades. We exploit the monthly attendance data in 2019 to analyze whether our intervention had any positive impact on enrollment rates in the post-intervention period, either because households realized the benefits of attending school or they expected to receive more cash in the future.[18] Using the pure experimental design, we find that the CCT treatment did not have any significant impact on the enrollment rates of the study participants. (Appendix D Table A19). However, conducting a sub-sample analysis across different grades and genders, we find that the SMS treatment arm had a positive impact on the enrollment rates of girls in higher grades, but the results are weakly significant.

Child Labor and Child Marriage

We use the following DiD specification to study the impact of the intervention on incidence of child labor and early marriage:

[18]Students who are not enrolled could either have dropped out of school or taken transfer to a different school.

$$\begin{aligned} Y_{it} &= \alpha + \gamma_0 \text{Endline}_t + \beta_1(\text{Gain}_i \times \text{Endline}_t) + \beta_2(\text{Loss}_i \times \text{Endline}_t) \\ &\quad + \beta_3(\text{SMS}_i \times \text{Endline}_t) + \theta Z_i + \varepsilon_{it}, \end{aligned} \tag{1.4}$$

where Y_{it} is the indicator variable for child labor (i.e., whether the child is engaged in a gainful activity[19]) or child marriage (i.e., whether the child is married). That is, Y_{it} takes a value of one if the child is working or married, and zero otherwise. Endline_t is an indicator variable for the endline survey, and Z_i is the household fixed effects. β_1, β_2 and β_3 are the coefficients of interest.

As reported in columns (1)–(3) of Table 1.6, we find that the intervention does not have much impact on incidence of child labor. This is true even when we break down the analysis by grades (not reported). However, because the definition of labor is referenced to the week preceding the survey, we are unable to capture the impact of the intervention on seasonal labor during the harvest or planting season. Hence, we cannot exclude the possibility that the seasonality in attendance impact observed in Figure 1.2 is driven by the reduction in seasonal child labor.

Column (4) of Table 1.6 provides the results for early marriage for girls. As the column shows, the Loss treatment reduces incidence of early marriage by 10.4 percentage points for girls, which is marginally significant. We further conduct a sub-sample analysis of female early marriage by grades and the impact of treatments are negative and large for grade 9 both in absolute value and relative to lower grades (Table A20 in Appendix D). In particular, the estimated reduction in female early marriage for grade 9 students due to the Loss treatment is 31.1 percentage points, which is significant both statistically and economically.

[19]The student's primary or secondary activity over the past week was employment in agriculture, forestry, aquaculture, employment in a wage/salaried position, other self-employment in production, business and service or performance of domestic duties.

Table 1.6: Impact of Intervention on Child Labor and Child Marriage

Dependent variable	Child labor			Child Marriage
	(1)	(2)	(3)	(4)
Endline	0.043	-0.011	0.097**	0.134***
	(0.028)	(0.034)	(0.044)	(0.049)
Gain × Endline	-0.010	0.042	-0.063	-0.051
	(0.038)	(0.047)	(0.060)	(0.064)
Loss × Endline	-0.002	0.031	-0.036	-0.104*
	(0.036)	(0.044)	(0.056)	(0.058)
SMS × Endline	-0.0371	-0.000	-0.075	-0.103*
	(0.036)	(0.048)	(0.053)	(0.059)
Observations	1,508	760	748	782
R-squared	0.515	0.491	0.543	0.523
Household FE	Yes	Yes	Yes	Yes
Gender	All	Male	Female	Female

Note: The dependent variable in the first three columns is “Child labor" while in the last column the outcome variable is “Child Marriage". “Child labor" takes a value of 1 if primary or secondary occupation of the child is wage/salaried employment, self-employment in agriculture, forestry, and aquaculture, other self-engagement (including family business) in production, business, and services, or domestic duties. “Child Marriage" takes a value of 1 if the child is married, and 0 otherwise. There was one girl child from the new cohort who was separated at baseline and remained so at endline. We assumed her marriage status as “unmarried". The Control treatment arm is the reference category in all regressions. The above specifications control for household level fixed effects. Standard errors are clustered at the individual level are given in parentheses. ***, **, and * denote statistical significance at 1, 5, and 10 percent levels, respectively.

Test Scores

We also administered a mathematics test for the study participants at the baseline and endline. The questions examined their competencies in basic arithmetic and geometry.[20] Higher attendance rates in school for the Gain and Loss treatment arms might have resulted in better learning outcomes. To test for that possibility, we estimate a value added model that includes the baseline test score, the child's anthropometric measures and several household level controls, and where attendance rate of the individual is instrumented for by treatment assignment. Both baseline and endline test scores are normalized relative to control mean and standard deviation for every cohort-school-grade combination.

$$\text{Score}_{it} = \alpha_0 + \alpha_1 \text{AttendanceRate}_i + \alpha_2 \text{Score}_{i0} + \alpha_3 \text{X}_i + \varepsilon_{it}, \quad (1.5)$$

where AttendanceRate_i is the attendance rate of individual i during our intervention years, Score_{it} is the mathematics test score for individual i at time t, where $t = 0$ corresponds to the baseline. The vector of covariates X_i includes child-level characteristics such as education level of the parents, gender, weight and height of the child, and unbalanced covariates at baseline. Since AttendanceRate_i is endogenous, we instrument it by an indicator variable for the treatment assignment. Table A21 in Appendix D shows that attendance rate has no statistically discernible impact on test scores. This finding is consistent with existing studies that tend to find that interventions to incentivize school attendance have no or only little impact on learning outcomes (McEwan, 2015; Fiszbein and Schady, 2009).

However, one must exercise caution when interpreting the results. We only

[20] Since the endline survey was conducted after our intervention was over and some children were no longer in school, the missing rate for the mathematics test at the endline was as high as 10 percent, but the attrition rates were not significantly different across the four treatment arms. There was no missing data for the mathematics test at the baseline.

examine the test score for mathematics and not other subjects. Further, as recent studies on the long-term impact of CCTs (e.g., Barham et al. (2018), Cahyadi et al. (2018), and Millán et al. (2020)) suggest, exposure to CCTs can positively influence labor market outcomes through higher educational attainment and changes in reproductive health outcomes for girls (see also Millán et al. (2019) for a review). Hence, it may be the case that higher attendance—and delayed marriage for girls—would improve the learning in subjects other than mathematics or open the door to higher educational attainment in the long run, even though the short-run impact on mathematics test scores is negligible.

Spending Patterns

During the baseline survey, households in the Gain and Loss treatment arms were asked questions on how they intend to spend the CCT amount on health, education, luxury, savings, and other expenses. Additionally, during disbursement at the end of each phase, they were asked to provide retrospective information on the actual spending in each of the above categories. While one cannot completely rule out the possibility of social desirability bias, reported spending on education from the endline survey was as high as 90 percent and 92 percent of the total cash transferred to the Gain and Loss treatment arms, respectively. This was considerably higher than the intended percentage quoted in the disbursement survey at the end of Phase 1, 2018, which were 75 percent and 69 percent, respectively. In contrast, the households in the Gain and Loss treatment arms reported that they intend to spend, respectively, 15 percent and 20 percent of the CCT amount on luxury expenses, but their actual spending was only 1 percent. Hence, the extra cash that the household received from the CCT intervention was mostly used to finance the education expenditures of the child.

1.8 Cost-effectiveness of CCT and SMS Treatments

The estimated impact of the SMS treatment was smaller than that of the Gain and Loss treatments and the difference is statistically significant (Table 1.2). However, the SMS treatment is much less expensive than CCT treatments from the policy-maker's perspective as the former does not involve cash transfers. Therefore, it is not obvious whether the SMS treatment is more or less cost-effective than the CCT treatments. Furthermore, the impact of the SMS treatment on attendance may potentially persist beyond the intervention period at least as strongly as the CCT treatments, even though this result is inconclusive (Table 1.3 columns (3) and (4)). Hence, SMS treatment may be a particularly attractive policy option in a country with very tight budget constraint. The SMS treatment may also be more politically palpable than CCT treatments since it merely provides information and the implementation cost is minimal. Hence, we consider the cost-effectiveness of our intervention over the two years.

The average transfer cost per student for the Gain CCT treatment was 1755.00 taka where as the same for the Loss CCT treatment was 1773.70 taka. The average non-transfer cost per student for the CCT treatment, which includes the costs of communication and transportation, was 188.65 taka and the corresponding figure for the SMS treatment was 134.40 taka (only communication costs). Using these figures and the impact estimates in column (1) of Table 1.2, we can estimate the total program cost per percentage point increase in attendance per student at 181.65 (=(1,755.00+188.65)/10.7), 175.21(=(1,773.70+188.65)/11.2), and 28.60(=134.40/4.7) taka for the Gain, Loss, and SMS treatments, respectively. Alternatively, since cash transfers do not change the total amount of resources in the population of interest, we could also omit the transfer cost in the calculation of the cost-effectiveness measure. In this case, the non-transfer program cost per percentage point increase in attendance per student is 17.63 (=188.65/10.7), 16.84 (=188.65/11.2), and 28.60 (=134.40/4.7) taka for the Gain, Loss, and SMS

treatments, respectively. While it is also common to use the latter measure or its reciprocal (e.g., García and Saavedra (2017)) as a cost-effectiveness measure, we argue that the former measure tends to be more relevant for policy-makers who tend to face binding resource constraints. Put differently, for policy-makers who only have a modest amount of resources to increase attendance, SMS treatment can be a good option.

It should be noted that the analysis above took the transfer amount as given. However, because there is a diminishing marginal impact of transfer, it is possible to increase the cost-effectiveness of the CCT interventions by changing the daily transfer amount. As detailed in Appendix C, our estimates from a quadratic model in transfer amount suggest that the most cost-effective amount of transfer turns out to be roughly around 20 taka per student per intervention day, even though the amount increases with the potential attendance probability in the absence of CCT program. However, note that this quadratic model does not differentiate between Gain and Loss treatment arms and treats them as one CCT treatment arm. This is admissible since the difference between Gain and Loss CCT is not statistically significant, and moreover, we are interested to study the impact of CCT at the intensive margin.

While it is difficult to convincingly determine how large the net benefits of our treatments are, it is still useful to understand the order of magnitude of the long-run benefits of our interventions. The results in Tables 1.3 and A19 in Appendix D indicate that the impacts on attendance and enrollment persist, even though the estimates are not always significant. To provide a lower bound of the benefits in terms of increase in wages, we take 4.6 percent as a conservative recent estimate of the Mincerean rate of return for secondary education (Rahman et al., 2019) and assume that the increase in the enrollment rate reported in column (1) of Table A19 lasts for a year.[21] Put differently, those who were enrolled in school as a result of the treatment are assumed to study one additional year

[21] Ito and Shonchoy (2020) report a higher estimate of 6.6 percent.

in comparison to the counterfactual situation without the treatment. Based on these assumptions, both the Gain and Loss treatments should lead to an increase in the logarithmic wage by 0.15 $(= 4.6 \times 0.032)$ log points whereas for the SMS treatment, it should lead to an increase by 0.33 $(= 4.6 \times 0.072)$ log points.

1.9 Conclusion

We have shown that the conventional Gain treatment increases morning attendance for secondary school students in Bangladesh by about 11 percentage points net of peer effects. The impact of the Loss treatment is higher than the conventional Gain treatment, even though the difference is not statistically significant. The SMS treatment also has a positive and significant impact on morning attendance by five percentage points. The results are similar when alternative measures of attendance are used. The estimated impacts of our treatments compare favorably to the mean impact of 5.75 percentage points derived from 22 evaluations of the impact of CCTs on secondary-school attendance reported in García and Saavedra (2017). Even though both the details of the program implementation and the program impacts are highly heterogeneous, our study appears to indicate the presence of 'low hanging fruits' to promote secondary-school attendance in our study area and possibly elsewhere in Bangladesh.

A heterogeneity analysis based on occupation reveals that the loss framing seems to be most effective for agricultural households when the transfer amount is sufficiently large, and is thus able to decrease the opportunity cost of attending school during the harvest season. We also find that the CCT treatment effects are higher for girls and for children in households who live further away from school, thus benefiting individuals at the margin. Analyzing the data on social network indicates significant peer effect in attendance but the effect sizes remain the same once such peer interactions are controlled for. Finally, though our intervention does not have any perceptible impact on learning outcomes, the

Loss and SMS treatments delay incidence of marriage for older girls in our sample. This result is further strengthened by the fact that the older girls in these treatment arms are more likely to stay enrolled in school even in the year following the intervention.

The ineffectiveness of the Loss treatment to achieve significant improvement in attendance over and above the conventional Gain treatment is possibly due to delayed rewards for households in the Loss treatment arm. Not giving them cash at the beginning of each phase would have failed to generate the desired endowment effect. Thus, future experimental studies on loss aversion can endow households with cash at the beginning of the intervention to generate an endowment effect. However, within the current framework, we do not find evidence of any adverse impact of the loss design on households. Also, the SMS treatment is more cost-effective than CCT treatment in terms of overall program costs while if we look at non-transfer program costs, loss framing is marginally more cost-effective than the conventional gain framing. Therefore, both loss framing and SMS nudges can be considered as alternative cost-effective approaches to promote attendance in schools, especially in the developing world where resources for policy interventions are typically limited.

2 Alcohol Consumption and Intimate Partner Violence: Causal Evidence from India[22]

2.1 Introduction

Global estimates published by the World Health Organization (WHO) indicate that about 1 in 3 women around the globe has been subject to physical and/or sexual violence in her lifetime. Intimate partner violence has been the most common form of any such violence and while it is a matter of global concern, women in the less developed and developing economies are probably worse affected. In this paper, I study the causal impact of alcohol consumption on incidence of physical and sexual intimate partner violence in India. Not only do gender disparities exist in India with regard to economic and social outcomes, the females have also traditionally been subject to various social malpractices, such as the sati and dowry system (Menon, 2020). In 2014, the WHO identified Indian drinkers as the most problematic in the world, in terms of total years of life lost to alcohol consumption.

Based on the medical literature, exposure to intimate partner violence can not only have adverse impacts on women's physical health but can also result in mental health concerns (Huth-Bocks et al., 2002), personality disorders (Pico-Alfonso et al., 2008), and worse child and adolescent outcomes (Evans et al., 2008). Further, it can also influence the dynamics of the relationship between the mother and her child (Levendosky et al. (2003) and Thiara and Humphreys (2017)). However, these studies have limitations in terms of small sample size and more importantly, the inability to derive a causal interpretation.

Increased employment opportunities for women and a declining wage gap in recent years have been able to mitigate the issue of intimate partner violence significantly (Aizer, 2010). However, it continues to be widespread and deserves

[22]I would like to thank Professor Tomoki Fujii for his invaluable comments and feedback. All mistakes remain mine.

the attention of policy makers in the developed and less developed world alike. Bowlus and Seitz (2006) show that women can have greater bargaining power in a marriage by being employed and prevent incidence of abuse, but once the marriage has become abusive, her first best option is to divorce her spouse. Another disconcerting fact about exposure to domestic violence is that it can often have intergenerational consequences (Pollak, 2004).

In light of the above, research that has looked into the impact of alcohol consumption on incidence of intimate partner violence has surprisingly been scarce. And the few papers that have explored the causal impact have found mixed results. For example, Markowitz (2000) used a reduced form equation with individual level fixed effects and showed that an increase in the price of alcohol led to lower incidence of violence against wives. Averett and Wang (2016) exploited exogenously determined interview dates on either side of the September 11 terrorist attack as an instrumental variable for alcohol consumption, and found no statistically significant effect of alcohol consumption on incidence of intimate partner violence. Angelucci (2008) used variation in the transfer amount of the *Oportunidades* program and found that while small transfers reduced alcohol consumption and were able to significantly decrease violence, large transfers led to increase in incidence of violence. There are a couple of studies that have looked into the impact of alcohol consumption on incidence of intimate partner violence in India. Luca et al. (2015) used data from the Indian National Family Health Survey (1998-99 and 2005-06) and the Indian National Crime Records Bureau (1980–2010) and found that state level ban on the commercial sale of alcohol was able to substantially reduce incidence of domestic violence. Luca et al. (2019) built on the above paper and used the variation in the minimum legal drinking age across states and observed that more stringent alcohol control measures led to lower rates of crime against women.

The use of instrumental variables to account for the possible endogeneity of substance use is very common. French and Popovici (2011) conduct a com-

prehensive literature review of the instrumental variables that have been used to account for the endogeneity of substance use. Some of the more commonly used instrumental variables are family characteristics such as drinking habits of parents, personal beliefs and traits such as religion or smoking habits and state level policies such as price of alcohol or state revenues from alcohol sale. However, family characteristics are not truly exogenous since parents' smoking/drinking habits can be correlated with family status. For example, if individuals from poorer households have a greater proclivity to drinking/smoking, family characteristics will not satisfy the exogeneity principle of instrumental variables. Second, though alcohol is considered as haram in Islam and therefore one can potentially use religion as an instrumental variable for alcohol consumption, I have individuals from multiple religions in the dataset and hence religion will not be a very strong predictor of alcohol consumption. Finally, availability of state wise data on alcohol price and alcohol revenue is relatively poor. Moreover, alcohol price varies within a given state based on the type of alcohol. Therefore, in this study, I use two instrumental variables by exploiting the state level variation in alcohol ban and minimum legal drinking age – state level instrument based on which state the individual resides in and an individual level instrument based on the person's age and place of residence – to account for the possible endogeneity of alcohol consumption.

The contributions of the paper to the existing literature are manifold. My study is an extension of Luca et al. (2015) and Luca et al. (2019) and instead of using just-identified models where they use alcohol ban and minimum legal drinking age across states respectively to instrument for husband's alcohol consumption, I use an overidentified model where I exploit both the variation in alcohol ban as well as the minimum legal drinking age across states in the same specification to identify the causal impact of alcohol consumption on incidence of intimate partner violence. Both of these variables are strong predictors of alcohol consumption, and using Sargan and Basmann's test of overidentifying

restrictions, I show that they do not violate the exogeneity principle and thus appear to be valid instruments

Second, I analyze the impact of husband's alcohol consumption on different facets of intimate partner violence - less severe physical violence, severe physical violence, and sexual violence. Previous studies do not differentiate between the type of violence that an individual has been exposed to. If one ignores the use of force at lower levels, one might underestimate the true impact of alcohol consumption on intimate partner violence. Therefore, it is imperative that one analyzes the impact of spouse's drinking habits on different forms of violence.

Third, I study the impact of alcohol consumption on several metrics of women empowerment such as freedom of movement, and bargaining powers within the household. Luca et al. (2019) control for these variables in their specification, but I treat each of these variables as outcome variables in themselves. It not only helps to circumvent the problem of "bad" controls but also provides a more holistic understanding of the impact of husband's alcohol consumption on women empowerment.

Fourth, the incidence of intimate partner violence could vary along several dimensions such as residence of the household (rural/urban), economic status of the household, disparity in education level between the female and her spouse, and previous exposure to violence. Previous studies that have tried to identify the impact of alcohol consumption on intimate partner violence have not addressed the impact heterogeneity across these dimensions. A heterogeneity analysis along the above dimensions reveals whether there is any differential impact, and this is of particular importance in designing effective policies that could potentially reduce incidence of intimate partner violence.

Finally, since I am exploiting state level variation in alcohol ban to instrument for alcohol consumption, the results of the study will be invalidated if individuals in states where alcohol was allowed were more regressive in their gender attitudes. If this were indeed true, then one cannot rule out the possibil-

ity that the results are not driven by alcohol consumption, but by poor gender attitudes, whereby men justify physical abuse of their partners, and women approve of the same. Earlier studies did not explicitly show that the alcohol ban was exogenous and rule out the possibility of the results being driven by regressive gender attitudes in states where alcohol is allowed.

I have a number of interesting findings from the analysis. Alcohol consumption by the husband increases incidence of less severe physical violence and severe physical violence by 55 percentage points and 23.6 percentage points respectively with there being no perceptible impact on sexual violence, when one uses weighted regressions. In general, metrics of women empowerment such as freedom of movement and decision making powers within the household are also adversely affected by spouse's alcohol consumption habits. I find that there is a vicious cycle of intimate partner violence whereby individuals who had previously been exposed to domestic abuse or live in poorly constructed houses are more at risk of facing intimate partner violence. Finally, I show that the results are not driven by regressive gender attitudes in states where alcohol is allowed. In fact, for men the gender attitudes are worse in states where alcohol ban was in place, and for women there is no systematic difference in the gender attitudes, reconfirming that the observed results are driven by alcohol consumption.

The rest of the paper is organized as follows. Section 2.2 has a discourse on the data employed in the study, and Section 2.3 discusses the methodology. Section 2.4 looks at the main results, and also performs heterogeneity analyses based on different household level characteristics such as place of residence (rural/urban), economic status, disparity in education level between partners, and previous exposure to violence. It also shows that the results in the study are not driven by worse gender attitudes in states where alcohol was allowed. Finally Section 2.5 concludes.

2.2 Data

I use the spatial variation in alcohol ban as well as minimum legal drinking age across states in India to instrument for husband's alcohol consumption. First, alcohol is banned in the states of Gujarat, Mizoram, and Nagaland in India. While the ban in Gujarat dates back to 1960, the bans in Nagaland and Mizoram came into effect in 1989 and 1997 through the Nagaland Liquor Total Prohibition Act and Mizoram Liquor Total Prohibition Act respectively. Moreover, Gujarat is the only state in the country where the convicted is subject to execution for the production and sale of homemade liquor that results in a death. However, in spite of the laws, there is high non-compliance in the above states, and particularly in the state of Gujarat, where alcohol is "freely" available (Thakkar and Dutta, 2013), and there have been instances of fatalities due to consumption of spurious liquor from time to time. Second, there is a considerable variation across states in India in the minimum legal drinking age. While in most states, the minimum legal drinking age is 21, it ranges from 18 to as high as 25 in some states. For more details on the variation in minimum legal drinking age across states in India, refer to Table A22 in Appendix D.

I use data from the third round of DHS (2005-06) in India to analyze the impact of husband's alcohol consumption on incidence of intimate partner violence.[23] More specifically, I use information from the couple's section which is the result of linking the men's and women's module where two individuals declared themselves as partners and completed individual interviews. The respondents in the women's module are ever-married females aged between 15 and 49 years. Within the women's module, I restrict the sample to households for whom the section on domestic violence was administered for females. The choice of households for administering the module on domestic violence was

[23]Compared to previous rounds of DHS, responses to questions on gender attitude are more comprehensive and complete in DHS (2005-06) while using the subsequent round of DHS (2015-16) yields similar point estimates of the impact of alcohol consumption on incidence of intimate partner violence (results available upon request).

random and only one woman from each of these randomly chosen households was chosen to receive the domestic violence module. Thus the unit of analysis in my study is a couple where both partners were interviewed, and the module on domestic violence was administered to the woman.

Also, the experience of intimate partner violence might be systematically different across women who have had one marriage or been in multiple marriages. Since the aim of the study is to identify the impact of husband's alcohol consumption on incidence of intimate partner violence, and the DHS data captures information on alcohol consumption of the current husband, the impact estimates might be confounded if we include women who have been married more than once and were subject to intimate partner violence due to their previous husband's alcohol consumption. Therefore, for the main results, I restrict the sample to women who have been married only once (98.12 percent of the original sample). Thus I have information on 28,285 couples in the study. However, I show that the findings are robust to inclusion of women who have been in multiple marriages.

The primary outcome variable is incidence of intimate partner violence. In particular, I look at different facets of violence namely less severe physical violence, severe physical violence, and sexual violence. The responses of the female can be one of the following: (i) never experienced violence (ii) experienced violence but not in last twelve months (ii) experienced violence sometimes during last twelve months, and (iii) experienced violence often during last twelve months. For the main analysis, I define exposure to intimate partner violence as a binary variable that takes a value of 1 if the individual experienced spousal violence at any point in the past, and 0 otherwise.

Based on administrative data, the rate of crime against women is considerably higher in states where alcohol is allowed (Figure 2.1). Our data shows similar patterns and the prevalence of intimate partner violence across states based on alcohol ban and minimum legal drinking age is given in Tables A23

and A24 of Appendix D respectively. The incidence of violence is consistently higher in states where alcohol is allowed, and the differences are statistically significant. Also, there is significant variation in incidence of intimate partner violence across states with different minimum legal drinking age. The results of the pairwise t-test for Table A24 can be made available upon request.

I also study the impact of alcohol consumption on different metrics of women empowerment such as freedom of movement and decision making powers within the household. In particular, the respondents are asked whether they are allowed to go to the market, health facility, and places outside the village, and their responses could vary from (i) allowed to go alone (ii) allowed to go with someone, and (iii) not allowed to go. With regard to decision making powers within the household, the respondents are asked who has a greater say in health related matters, regular and large purchases, and visits to family and friends. The possible responses range from (i) respondent alone (ii) respondent and husband together (iii) husband or someone else. I derive an ordinal measure for each of the above variables such that more freedom and better decision making powers are associated with a larger number.

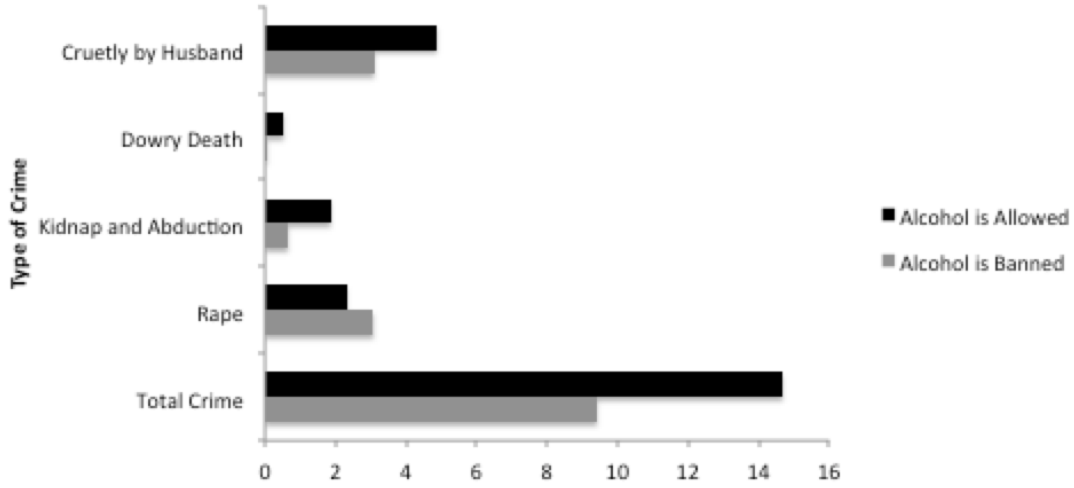
2.3 Methodology

Since alcohol consumption is endogenous, I use an overidentified model and instrument for alcohol consumption by the state wise variation in alcohol ban as well as minimum legal drinking age. The first stage equation is thus given by:

$$\text{Alcohol}_{\text{i}} = \beta_0 + \beta_1 \text{Allowed}_{\text{s(i)}} + \beta_2 \text{LegalAge}_{\text{s(i)}} + \beta_3 \text{H}_{\text{i}} + \phi_i \qquad (2.1)$$

where Alcohol_i is a dummy variable that takes a value of 1 if the husband in couple 'i' consumes alcohol, $\text{Allowed}_{s(i)}$ is a dummy variable that take a value of 1 if the individual 'i' is from a state where alcohol is allowed, and $\text{LegalAge}_{s(i)}$

Figure 2.1: Incidence of Crime Against Women in States where Alcohol is Allowed versus States where Alcohol is Banned



Note: (National Crime Records Bureau, 2008). The numbers in the x-axis show the the incidence of crime for every 100,000 units of the population. Gujarat, Mizoram, and Nagaland are the states where alcohol is banned.

is an individual specific binary variable that takes a value of 1 if the age of the husband is above the minimum legal drinking age in the state of residence in the year of survey. Thus, in our study sample, we have three kinds of individuals - (i) individuals in states where alcohol is allowed and they are of legal age to drink (ii) individuals in states where alcohol is allowed but they are not of legal drinking age, and (iii) individuals in states where alcohol is banned and hence no one is allowed to drink, irrespective of age. Thus for individuals, in states where alcohol is not allowed, the ban on alcohol acts as the binding constraint. Additionally, I control for characteristics of the couple including those of the female (age, education level, total number of children, pregnancy status) and her spouse (age and education level) and also some household level attributes (number of household members, place of residence, age of household head, religion and caste of household, and structure of house) denoted by H_i.

In the second stage, I regress incidence of intimate partner violence on alcohol consumption, and thus the main coefficient of interest is α_1.

$$Y_i = \alpha_0 + \alpha_1 \text{Alcohol}_i + \alpha_2 H_i + \varepsilon_i \quad (2.2)$$

While analyzing the impact of alcohol consumption on intimate partner violence, Y_i denotes exposure to physical violence (less severe and severe), and sexual violence. I also use the same specification to study the effect of alcohol consumption on other metrics of women empowerment such as freedom of movement, and decision making powers within the household.

Finally, as a robustness check, I use probability weights from the domestic violence module to make the sample more representative of the total population. This is particularly important since there is a tendency to oversample minority individuals in a given population, and therefore one might get biased estimates if one does not use weights to adjust for the relative importance of each observation. For example, in this study, two of the states where alcohol is banned, namely Nagaland and Mizoram, are relatively less populated states in the country and unless one uses probability weights to adjust for the relative importance of households from these two states, one might overestimate the impact of alcohol consumption on intimate partner violence. Therefore for the main specification, I report both weighted and unweighted results.

2.4 Results

Main Findings

Alcohol consumption must be highly correlated with a ban on alcohol as well as the minimum legal drinking age across states to satisfy the relevance principle of instrumental variables. The first stage results show that availability of alcohol is strongly correlated with alcohol consumption. In states where alcohol is allowed, men are 22 percentage points more likely to consume alcohol than they are in states where alcohol is banned (Column 4 of Table A25 in Ap-

pendix D). The variation in minimum legal drinking age across states in India is also a strong predictor of alcohol consumption (Table A26 in Appendix D). Thus the spatial variation in both alcohol ban and minimum legal drinking age have strong predictive power for drinking habits of men in my study.

The main results of the study are shown in Table 2.1. Unless otherwise mentioned, all the results hold true only for women who are currently married, and have had only one marriage. Columns (1)-(3) show the impact of alcohol consumption on incidence of intimate partner violence when the observations are not weighted where as columns (4)-(6) use weights to adjust for oversampling. As expected, once probability weights are used to make the sample more representative of the actual population, the point estimates become smaller. In the specifications, where sampling weights are used, alcohol consumption leads to an increase of less severe physical violence by 55 percentage points and severe physical violence by 23.6 percentage points. I do not find any impact on sexual violence, but its absence, in part, can be attributed to the confounding interpretation of severe physical violence and sexual violence. Intimate partner violence is also found to be more prevalent in rural India and is more common among Muslim households. Women who have higher educational attainment are also less likely to be victims of domestic abuse. The number of children that a woman has is strongly and positively correlated with incidence of intimate partner violence. However, since one cannot randomize place of residence, religion or education, these are only associations and one should not infer causality. The results are similar both qualitatively and quantitatively if we run the regressions for the entire sample by including women who have had multiple marriages (Table A27 in Appendix D).

I further decompose less severe physical violence and severe physical violence into different uses of force. If one ignores the use of force at lower levels, one might underestimate the true causal impact of alcohol consumption on incidence of intimate partner violence. While being slapped appears to be a very

Table 2.1: Impact of Alcohol Consumption on Intimate Partner Violence

Dependent variable	Less severe (1)	Severe (2)	Sexual (3)	Less severe (4)	Severe (5)	Sexual (6)
Alcohol	0.608***	0.273***	0.116***	0.550***	0.236***	0.064
	(0.066)	(0.040)	(0.032)	(0.082)	(0.046)	(0.043)
Age of female	-0.001	-0.000	-0.001	-0.002	-0.000	-0.000
	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)
Female has primary education	-0.013	0.001	-0.009*	-0.027**	-0.008	-0.0201***
	(0.010)	(0.006)	(0.005)	(0.013)	(0.009)	(0.007)
Female has secondary education	-0.085***	-0.037***	-0.019***	-0.086***	-0.034***	-0.024***
	(0.009)	(0.005)	(0.004)	(0.013)	(0.008)	(0.007)
Female has higher education	-0.160***	-0.047***	-0.031***	-0.170***	-0.050***	-0.044***
	(0.016)	(0.010)	(0.008)	(0.020)	(0.011)	(0.009)
Number of children	0.034***	0.012***	0.006***	0.036***	0.016***	0.007***
	(0.002)	(0.001)	(0.001)	(0.003)	(0.002)	(0.002)
Female is pregnant	-0.004	-0.008	-0.003	-0.025	-0.016	-0.011
	(0.012)	(0.008)	(0.006)	(0.018)	(0.011)	(0.009)
Age of husband	-0.001	-0.000	-0.000	-0.001	-0.001	-0.001*
	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)
Husband has primary education	0.015	0.002	0.002	0.032**	0.008	0.002
	(0.010)	(0.006)	(0.005)	(0.014)	(0.010)	(0.008)
Husband has secondary education	-0.002	-0.012*	-0.004	0.013	-0.013	-0.003
	(0.011)	(0.006)	(0.005)	(0.015)	(0.010)	(0.008)
Husband has higher education	-0.009	-0.010	0.008	0.023	-0.011	0.001
	(0.017)	(0.010)	(0.008)	(0.025)	(0.015)	(0.012)
Observations	28,285	28,285	28,285	28,285	28,285	28,285
Weights	No	No	No	Yes	Yes	Yes
Control Mean	0.169	0.042	0.035	0.169	0.042	0.035
Sargan p-value	0.7870	0.1643	0.6943	-	-	-
Basmann p-value	0.7871	0.1644	0.6944	-	-	-

Note: The dependent variables are binary outcomes that take a value of 1 if the female experienced intimate partner violence anytime in the marriage, and 0 otherwise. “Alcohol" takes a value of 1 if the husband drinks alcohol, and 0 otherwise. All of the above specifications control for female, husband, and household characteristics. ‘Control Mean’ denotes mean intimate partner violence in states where alcohol is banned. Sargann and Basmann’s p-values cannot be obtained when using probability weights in a regression. Robust standard errors clustered at the primary sampling unit (PSU) level are given in parentheses. ***, **, and * denote statistical significance at 1, 5, and 10 percent levels, respectively.

common form of domestic abuse, the point estimates for being strangled or being threatened with a knife/gun are considerably smaller but still positive and highly significant (Table A28 in Appendix D).

Husband's alcohol consumption not only has an adverse impact on incidence of intimate partner violence but at the same time it can also have a debilitating effect on women, through restricted movement and less decision making powers within the household. Most studies previously control for these factors when trying to find the impact of alcohol consumption on intimate partner violence, but these are typically "bad controls" since freedom of movement and bargaining powers within the household are outcomes in themselves. Controlling for the characteristics of the wife, her husband, and the household, it is seen that alcohol consumption by the husband has a significant negative impact on freedom of movement as well as decision making powers of the wife within the household (Table 2.2).

Are the Results Driven by Differences in Gender Attitude?

Since I exploit the exogenous variation in alcohol ban across states in India to determine the causal impact of alcohol consumption on intimate partner violence, the results of the study will be invalidated if the ban on alcohol was selective and was implemented in states where people were more progressive. For example, if individuals in states where alcohol is allowed have regressive gender attitudes, then the results in the study might not be driven by drinking habits of the husband but by regressive gender attitudes. Hence, I use the following specification to test for whether the gender attitudes are worse in states where alcohol is allowed.

$$\text{Beating not justified}_{is} = \beta_0 + \beta_1 \text{Alcohol is allowed}_{is} + \beta_2 \text{H}_{\text{is}} + \beta_3 \text{W}_{\text{is}} + \beta_4 \text{M}_{\text{is}} + \varepsilon_{is} \tag{2.3}$$

Table 2.2: Impact of Alcohol Consumption on Women Empowerment

Dependent variable	Freedom of movement			Decision making power			
	Market	Health	Outside	Health	Large purchase	Daily purchase	Visits
Alcohol	-0.980***	-0.244*	-0.675***	-0.489**	0.001	-1.046***	-0.376***
	(0.166)	(0.137)	(0.150)	(0.196)	(0.130)	(0.230)	(0.139)
Age of female	0.015***	0.011***	0.011***	0.009***	0.007***	0.011***	0.005***
	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)	(0.001)
Female has primary education	0.003	0.050***	0.041**	0.026	0.044***	0.084***	0.080***
	(0.022)	(0.015)	(0.017)	(0.021)	(0.016)	(0.024)	(0.016)
Female has secondary education	0.050**	0.099***	0.057***	0.103***	0.079***	0.098***	0.105***
	(0.022)	(0.015)	(0.019)	(0.022)	(0.016)	(0.026)	(0.017)
Female has higher education	0.212***	0.236***	0.218***	0.176***	0.141***	0.120***	0.176***
	(0.037)	(0.028)	(0.033)	(0.037)	(0.029)	(0.047)	(0.030)
Number of children	0.016***	0.017***	0.001	0.018***	0.010**	0.020***	0.004
	(0.006)	(0.004)	(0.004)	(0.005)	(0.004)	(0.006)	(0.004)
Female is pregnant	-0.017	-0.046**	-0.025	-0.041	-0.065***	-0.066**	-0.019
	(0.028)	(0.020)	(0.023)	(0.028)	(0.018)	(0.031)	(0.021)
Age of husband	0.001	0.003***	0.005***	0.002	0.006***	0.007***	0.009***
	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)
Husband has primary education	-0.030	-0.002	-0.040**	-0.011	-0.020	-0.019	0.002
	(0.023)	(0.016)	(0.019)	(0.022)	(0.016)	(0.026)	(0.018)
Husband has secondary education	-0.124***	-0.053***	-0.107***	-0.112***	-0.052***	-0.161***	-0.057***
	(0.026)	(0.019)	(0.022)	(0.027)	(0.019)	(0.032)	(0.021)
Husband has higher education	-0.219***	-0.091***	-0.181***	-0.159***	-0.051	-0.321***	-0.120***
	(0.045)	(0.036)	(0.040)	(0.049)	(0.033)	(0.057)	(0.034)
Observations	28,282	28,279	28,280	28,094	27,813	27,823	27,916
Control Mean	1.525	1.534	1.363	1.946	1.709	2.065	1.805

Note: The dependent variables are ordinal outcomes such that higher the value greater the women empowerment. The responses to freedom of movement in going to market, health facility, and outside the community range from allowed to go alone, allowed to go with someone, and not allowed to go. The responses to having a say in health issues, large purchases, daily purchases, and visits to family and friends range from allowed to decide alone, jointly with husband, and have no say. “Alcohol" takes a value of 1 if the husband drinks alcohol, and 0 otherwise. All of the above specifications control for female, husband, and household characteristics and adjust for weights from the domestic violence module. ‘Control Mean’ denotes average women empowerment in states where alcohol is banned. Robust standard errors clustered at the primary sampling unit (PSU) level are given in parentheses. ***, **, and * denote statistical significance at 1, 5, and 10 percent levels, respectively.

where Beating not justified$_{is}$ is a dummy variable that take a value of 1 if individual 'i' in state 's' does not justify beating his wife, and Alcohol is allowed$_{is}$ is a dummy variable that take a value of 1 if the individual 'i' is from a state where alcohol is allowed. I additionally control for female, husband, and household level characteristics that might explain the gender attitudes. In particular, Beating not justified$_{is}$ takes a value of 1 if the husband does not justify beating his wife due to one of the following actions of the wife – (i) goes outside without informing her husband (ii) neglects children (iii) argues with husband (iv) refuses to have sex (v) does not cook well. I additionally define another binary variable that takes a value of 1 if the husband justified beating his wife on any of the above grounds. Surprisingly, men in states where alcohol is allowed have more progressive gender attitudes and do not justify beating their wives (Table 2.3). Thus, the impact estimates that are observed are not a result of regressive gender attitudes of men in states where alcohol is allowed.

However, incidence of intimate partner violence might also depend upon the gender attitudes of women. For example, if women are more submissive in states where alcohol is allowed and justify being beaten by men, it could potentially lead to higher incidence of intimate partner violence. On the other hand, incidence of intimate partner violence might also be high if women are more conscious of their rights and do not justify beating beaten at any cost. Essentially, there should not be any systematic difference in gender attitudes of women between states where alcohol is allowed and where alcohol is banned. I use the same specification as in eq. (2.3) and find that there are no systematic differences in gender attitudes of women between states where alcohol is allowed and where alcohol is banned (Column (6) of Table A29 in Appendix D), on average.

Table 2.3: Are Gender Attitudes of Men Worse in States where Alcohol is Allowed?

Dependent variable	Husband does not justify beating wife when she					Does not justify beating
	Goes outside	Neglects children	Argues with husband	Refuses sex	Cooks bad	
	(1)	(2)	(3)	(4)	(5)	(6)
Alcohol is allowed	0.092***	0.181***	0.180***	0.052***	0.124***	0.212***
	(0.024)	(0.028)	(0.029)	(0.017)	(0.027)	(0.027)
Age of female	0.003***	0.005***	0.004***	0.002***	0.001	0.006***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Female has primary education	0.041***	0.028**	0.042***	-0.007	0.023***	0.034***
	(0.011)	(0.012)	(0.011)	(0.007)	(0.008)	(0.013)
Female has secondary education	0.079***	0.059***	0.065***	0.007	0.022***	0.084***
	(0.010)	(0.012)	(0.011)	(0.007)	(0.008)	(0.013)
Female has higher education	0.106***	0.137***	0.104***	0.013	0.036***	0.161***
	(0.015)	(0.017)	(0.015)	(0.009)	(0.011)	(0.020)
Number of children	-0.001	0.007**	-0.006*	0.001	-0.002	0.001
	(0.003)	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)
Female is pregnant	-0.006	0.026	-0.021	-0.006	-0.049***	-0.005
	(0.016)	(0.017)	(0.017)	(0.010)	(0.015)	(0.018)
Age of husband	0.000	-0.003***	0.000	-0.001*	0.000	-0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Husband has primary education	0.038***	0.029**	0.030**	0.009	0.022**	0.034***
	(0.013)	(0.013)	(0.013)	(0.008)	(0.010)	(0.013)
Husband has secondary education	0.106***	0.104***	0.081***	0.033***	0.052***	0.122***
	(0.012)	(0.012)	(0.012)	(0.008)	(0.009)	(0.013)
Husband has higher education	0.192***	0.200***	0.152***	0.056***	0.088***	0.246***
	(0.015)	(0.017)	(0.016)	(0.008)	(0.013)	(0.018)
Observations	28,189	28,191	28,084	28,053	28,206	27,772
R-squared	0.058	0.054	0.054	0.019	0.034	0.079
Control Mean	0.731	0.502	0.635	0.888	0.837	0.418

Note: The dependent variables are binary outcomes that take a value of 1 if beating is not justified, and 0 otherwise. “Alcohol allowed" takes a value of 1 if the individual is from a state where alcohol is allowed, and 0 otherwise. All of the above specifications control for female, husband, and household characteristics and adjust for weights from the domestic violence module. ‘Control Mean’ denotes average gender attitudes of men in states where alcohol is banned. Robust standard errors clustered at the primary sampling unit (PSU) level are given in parentheses. ***, **, and * denote statistical significance at 1, 5, and 10 percent levels, respectively.

Heterogeneity Analysis

The impact of alcohol consumption on incidence of intimate partner violence might vary along several dimensions such as place of residence (rural/urban), economic status of the household, disparity in education level between the wife and her spouse, and previous exposure to domestic violence. A subsample analysis will help one capture the treatment heterogeneity along these dimensions.

First, incidence of intimate partner violence could potentially vary between rural and urban households. Women in rural India are generally less empowered and thus are more susceptible to domestic abuse. As can be seen from Table 2.4, the impact of alcohol consumption on intimate partner violence is mostly driven by rural households. While husband's drinking habit results in a 67 percentage point increase in the incidence of less severe violence in rural India, the point estimate is considerably lower for urban households but still high at about 28.4 percentage points and statistically significant. For severe physical violence, the impact is only significant for rural households.

Second, women in poorer households might be worse affected by incidence of intimate partner violence. Since there is no information in DHS data regarding household income, I use the quality of house structure as a proxy for economic status of a household. Couples who lived in establishments with no walls or in houses made of cane, mud or grass were considered to be poor; couples who lived in houses that were constructed of bamboo, plywood, unburnt bricks, and cardboard were considered as middle income, and couples residing in houses made of cement and burnt bricks belonged to the high income group. The incidence of both less severe and severe physical violence was significantly higher in poorer households as compared to households who lived in permanent and stable constructions (Table A30 of Appendix D). Thus, women from less privileged background, who live in the rural parts of India and belong to the lower socioeconomic strata are worse affected by incidence of intimate partner

Table 2.4: Heterogeneity Analysis by Place of Residence

Dependent variable	Less severe		Severe		Sexual	
	Rural	Urban	Rural	Urban	Rural	Urban
Alcohol	0.670***	0.284**	0.299***	0.108	0.088	0.012
	(0.112)	(0.138)	(0.058)	(0.074)	(0.066)	(0.065)
Age of female	-0.001	-0.004**	0.001	-0.003**	-0.000	-0.001
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Female has primary education	-0.027	-0.029	-0.007	-0.008	-0.015*	-0.040***
	(0.017)	(0.021)	(0.011)	(0.015)	(0.008)	(0.012)
Female has secondary education	-0.063***	-0.119***	-0.031***	-0.034**	-0.012	-0.049***
	(0.018)	(0.021)	(0.010)	(0.013)	(0.009)	(0.012)
Female has higher education	-0.172***	-0.188***	-0.071***	-0.039**	-0.048***	-0.065***
	(0.035)	(0.027)	(0.017)	(0.016)	(0.015)	(0.014)
Number of children	0.035***	0.040***	0.016***	0.018***	0.006**	0.001***
	(0.004)	(0.006)	(0.003)	(0.004)	(0.003)	(0.003)
Female is pregnant	-0.027	-0.030	-0.019	-0.015	-0.017	0.005
	(0.025)	(0.025)	(0.015)	(0.016)	(0.013)	(0.013)
Age of husband	-0.001	0.000	-0.002*	0.001	-0.002**	-0.000
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Husband has primary education	0.035**	0.016	0.014	-0.015	0.001	0.014
	(0.018)	(0.028)	(0.012)	(0.020)	(0.010)	(0.013)
Husband has secondary education	0.038*	-0.054**	0.002	-0.057***	-0.014	0.029*
	(0.020)	(0.026)	(0.012)	(0.020)	(0.011)	(0.015)
Husband has higher education	0.073**	-0.071**	0.020	-0.071***	-0.009	0.029
	(0.036)	(0.035)	(0.021)	(0.023)	(0.020)	(0.018)
Observations	14,806	13,479	14,806	13,479	14,806	13,479
Control Mean	0.172	0.166	0.046	0.038	0.040	0.029

Note: The dependent variables are binary outcomes that take a value of 1 if the female experienced intimate partner violence anytime in the marriage, and 0 otherwise. “Alcohol" takes a value of 1 if the husband drinks alcohol, and 0 otherwise. All of the above specifications control for female, husband, and household characteristics and adjust for weights from the domestic violence module. ‘Control Mean’ denotes mean intimate partner violence in states where alcohol is banned. Robust standard errors clustered at the primary sampling unit (PSU) level are given in parentheses. ***, **, and * denote statistical significance at 1, 5, and 10 percent levels, respectively.

violence. Hence, from a policy perspective, there needs to be more attention given to these disadvantaged sections of society since incidence of domestic abuse is more pervasive in these households.

Third, along a similar line of thought, women who have grown up in households with prevalence of domestic abuse might be at greater risk of experiencing the same (Markowitz, 2001; Holt et al., 2008). This could be a result of positive assortative mating or the fact that one might internalize domestic abuse having grown up in a similar environment. Though most women in the study were not raised in households where their father used to beat their mother, there is evidence that incidence of severe physical violence is significantly higher in households where the woman was exposed to intimate partner violence while growing up (Table A31 of Appendix D). This is also very important from a policy perspective since it hints at the possibility of a vicious cycle of domestic abuse, whereby women with past exposure to intimate partner violence tend to marry in to families where they are more likely to experience abuse. However, intimate partner violence is also not completely intergenerational as there are women who have had no exposure to domestic abuse in the past but are now victims of less severe physical violence.

Fourth, incidence of intimate partner violence might also depend upon the level of assortative mating. For example, if the woman in the marriage is less educated than her spouse, she might be more at risk of experiencing domestic abuse. Hence I perform a heterogeneity analysis based on whether the educational attainment of the wife is less than, equal to or more than that of her spouse. The incidence of domestic abuse is unambiguously less in households where the wife and her husband have similar education levels (Table A32 of Appendix D). Surprisingly however, the point estimate of severe physical violence is higher in households where the female is more educated than her spouse.

2.5 Conclusion

Intimate partner violence is a serious concern in the developing and developed world alike and given the gravity of the problem at hand, it is surprising that the economics literature that has tried to uncover the causes behind it is considerably sparse. Husband's alcohol problem is one of the contributing factors to prevalence of intimate partner violence, and this is particularly true in India where men are often reckless with regards to their drinking habits. In this study, I find the causal impact of alcohol consumption on incidence of intimate partner violence using DHS data for India for the year 2005-06. I use an overidentified model where I instrument for husband's alcohol consumption by the spatial exogenous variation in alcohol ban and minimum legal drinking age across states. Both these instruments are good predictors of husband's alcohol consumption and also satisfy the exogeneity principle.

I study the impact of alcohol consumption on different facets of intimate partner violence and type of force used – less severe physical violence, severe physical violence, and sexual violence. Husband's alcohol consumption increases incidence of less severe physical violence by 55 percentage points and severe physical violence by 23.6 percentage points with there being no perceptible impact on sexual violence. Not only does husband's alcohol consumption lead to higher incidence of physical abuse but it also weakens the status of women in general through restricted movement and less decision making powers in the household. Since I use the spatial variation in alcohol ban across states in India to instrument for husband's alcohol consumption, the results of my study will be invalidated if the gender attitudes of men and women are worse in states where alcohol is allowed. In fact, I find evidence that men are more progressive with regards to their gender attitudes in states where alcohol is allowed and there is no systematic difference in gender attitudes of women between states where alcohol is allowed and where alcohol is banned. This is reassuring since the

impact estimates that are observed can then be attributed to husband's alcohol consumption.

I find that it is often the disadvantaged women in society who are worse affected by incidence of intimate partner violence. A heterogeneity analysis reveals that incidence of domestic abuse is higher in rural India and also in households that are considerably poorer. Further, women who have been exposed to intimate partner violence in their early life due to an abusive relationship between their parents are also more likely to be victims of intimate partner violence in their conjugal life. Positive assortative mating where the educational attainments of the women and her spouse are similar can however mitigate the incidence of intimate partner violence.

Thus from a policy perspective it is essential that one addresses the issue of intimate partner violence, and particularly for women who belong to the more disadvantaged sections of society. Since a ban on alcohol is not politically palatable and increasing the minimum legal age for drinking does not necessarily resolve the problem but only delays the inevitable, governments need to devise policies that can empower women, through better education and income generating opportunities. This can further break the vicious cycle of intergenerational transmission of intimate partner violence. At the same time, men can be made more aware of the harmful effects of binge drinking through educational campaigns, and advertisements. Depending upon the availability of good data, future studies can look into the effects of alcohol consumption at the intensive margin. Drinking in moderate quantities might not necessarily be bad and the high impact estimates that are observed are possibly a result of binge drinking. Analyzing the impact at the intensive margin can be beneficial and can help policy makers determine the "optimal" amount of alcohol consumption that will not lead to incidence of intimate partner violence.

3 Government Benefit Programs and Parental Investment in Education: Evidence from the Mid Day Meal Scheme in India[24]

3.1 Introduction

The mid day meal program in India is the largest school-feeding program in the world, feeding about 115 million children every school day (Tibrewala, 2021). In 1995, though the central government of India mandated the provision of free school meals to all children in public primary schools via the National Program of Nutritional Support to Primary Education, the compliance rates among the states were very poor. A few years later, in 2001, seven districts in the country were hit by severe droughts leading to many deaths due to starvation. The People's Union for Civil Liberties (PUCL) then filed a case against the Government of India arguing that the stock of food grains in the country was much more than the storage capacity, and that there was a need for expansion of the different statutory food and nutrition programs including the mid day meal scheme in schools. Finally, the Supreme Court of India issued an interim order on November 28, 2001 stating that "Every child in every government and government-assisted school should be given a prepared mid day meal".[25] Nevertheless, in spite of the Supreme Court order, the mid day meal program was implemented in a staggered manner across different states over the next five years, and by 2006 all students in primary government and government-aided schools in all states became recipients of the mid day meal scheme. The mid day meal guidelines specified that each student should receive 100 grams of wheat or rice, 20 grams of pulses, 50 grams of vegetables and 5 grams of fat per day for a total calorie

[24]This paper has been co-authored with Arpita Khanna (Singapore Management University). We sincerely thank Professor Tomoki Fujii for his comments and feedback. All mistakes remain ours.

[25]Supreme Court Order of November 28, 2001, Record of Proceedings Writ Petition (Civil No). 196 of 2001

intake of 300 kilo calories (MHRD, Government of India, 2016). In 2009, the total cost of providing the meal was Rs 2.90 (approximately US$ 0.032) per child per day, which was inclusive of the cooking costs, and the cost of labor and management. Of the total costs, about 75 percent was borne by the central government while the residual 25 percent was borne by the state government.

Our study primarily contributes to three strands of literature - first, we understand how individuals respond to government benefit programs, and whether their actions align with the goals of the policy. Past papers have studied the impact of public transfers, and in particular, school feeding programs on nutrition expenditures by parents in China (Chen et al., 2020), Guatemala (Islam and Hoddinott, 2009), India (Afridi, 2005), and Philippines (Jacoby, 2002), and have found mixed evidence of resource reallocation in response to such government benefit programs. While economic incentives are a powerful policy instrument, policy makers also need to factor in how individuals might react to such interventions. For example, in a randomized controlled trial study by Gneezy and Rustichini (2000) in Israel, parents in the treatment arm, who had to pay a fine for not coming to school on time to receive their children, incurred more fine than the parents in the control arm, who were not subject to any such fine. The parents in the treatment arm justified their lack of punctuality since they were already paying a fine now. While the mid day meal scheme was introduced to address nutrition deficiency and to increase enrollment and attendance rates in government schools, if parents transferred their children from better quality private schools to lower quality government schools just to receive a mid day meal, it might have adverse effects on the children. Therefore, it is essential to understand how parents react to such incentives from the government and how their actions, in turn, might have an effect on the learning and health outcomes of their children.

Second, we aim to analyze how parents' investment decisions in their children's education affect their learning and health outcomes. There is a vast liter-

ature that has studied the impact of early life interventions on child health and learning outcomes (McEwen, 2003; Bharadwaj et al., 2013; Haire-Joshu and Tabak, 2016) through both experimental and quasi-experimental means. Exposure to such educational and health programs in early life usually leads to better outcomes not just in the short run but also in terms of favorable long term labor market outcomes (Johnson and Schoeni, 2011). Parents' investment in education is perhaps the most important among all such early life interventions (Yeung et al., 2002; Francesconi and Heckman, 2016; Abufhele et al., 2017), and therefore it is important to understand from a policy perspective whether parental investment in early life leads to better learning and health outcomes.

Finally, several studies have looked at the impact of school feeding programs on a wide range of outcomes such as school enrollment rates, absenteeism, and learning and health outcomes. Alderman and Bundy (2012) provides a comprehensive review of the impact of these programs on the educational and health outcomes of primary school going children. In particular, many studies have looked into the impact of the mid day meal program in India on child health (Khera, 2013; Anitha et al., 2019; Mohan and Thakkar, 2019) and learning outcomes (Bonds, 2012; Chakraborty and Jayaraman, 2019). However, the results have been mixed at the best. While there has been a more general consensus on the improved enrollment rates and higher attendance as a result of the mid day meal scheme (Jayaraman and Simroth, 2015; Afridi, 2011), the impact of the program on health outcomes has been ambiguous (Singh, 2008; Deodhar et al., 2010).

Thus, our study makes the following contributions to the existing literature. First, the staggered implementation of the mid day meal program, which is arguably exogenous, allows us to find the causal impact of a government benefit program on parental investment in education and understand how parents react to such economic incentives. While the past literature has looked into the impact of school feeding programs on resource allocation in food expenses, our

study is unique and studies the impact of such schemes on educational expenses. Thus, our study aims to understand the impact of the provision of complementary meals in schools on educational expenses, and captures an effect that is less mechanical. Second, we analyze how this differential investment in education expenditures, if any, affects the learning and health outcomes of the children. Thus, our study is holistic and tracks how parents react to government benefit programs, and how their responses, in turn, affect the learning and health outcomes of the child. Third, our paper also contributes to the literature on gender bias and finds evidence of whether there is any disparity in educational expenditure between the boy and the girl child. In particular, we aim to understand how parents decide on the education investment of their children based on the gender composition of the siblings, and in response to the mid day meal program.

We have a number of interesting findings from our analysis. First, exposure to the mid day meal program reduces expenditure on school fees by 16 percent, with there being no perceptible impact on expenses on other items such as books, uniform, and transportation. Second, this reduction in school fees can be attributed to a 4.4 percentage point increase in enrollment in government schools and a 3.2 percentage point decrease in enrollment in private schools, which indicates that parents move their children from private schools to government schools in response to the mid day meal program. Third, such a transfer does not lead to any improvement in learning or health outcomes for children who are eligible to receive the mid day meal in government schools. However, we do not find evidence of any gender discrimination in educational expenditures between the boy and the girl child. Finally, conducting a heterogeneity analysis on educational expenditures and likelihood of being enrolled in a government/private school across different consumption quartiles, we find that the poorer households are more likely to transfer their children from private schools to government schools in response to the mid day meal program, with the greatest impact happening in the second consumption quartile.

The rest of the paper is organized as follows. In Section 3.2, we discuss the data sources and our relevant study sample. We then present the methodology and identification strategy in Section 3.3. Section 3.4 describes the main results and findings of our study, including a brief discourse on whether there is any gender discrimination in education related expenditures. Section 3.5 performs robustness checks for our main results and Section 3.6 provides the results from heterogeneity analyses based on consumption quartile and place of residence of the household. Finally, Section 3.7 concludes.

3.2 Data

We use data from the nationally representative Indian Human Development Survey (IHDS), a unique panel survey that interviewed around 42,152 households across 1,420 villages and 1,042 urban neighborhoods in India in the years 2005-06 and 2011-12. IHDS covers a range of topics such as income, agriculture, consumption, employment, education and health among others. We use data from the 2005-06 round of IHDS, primarily focusing on outcomes concerning education.

There are several advantages of using the IHDS data for our study. First, unlike most other survey data that have household level information, the IHDS data has child level information on the investments made by parents in educational inputs such as school fees, books, stationery, uniform, school transport etc. This allows us to answer our main research question of how parents alter their investment decisions regarding their children's education in response to the program. Second, the first round of IHDS was conducted in 2005-06, before the mid day meal program was implemented in all states. This allows us to exploit the variation in exposure to the mid day meal scheme across cohorts in different states and also have a pure comparison group that includes eligible children in states who were not exposed to the mid day meal program till then.

Third, IHDS also conducted short reading, writing, and arithmetic tests on all available children in the age bracket of 8-11 years, which lets us see the impact of the mid day meal program on learning outcomes. Finally, the study collected comprehensive individual level information such as education level, parents' education level, type of school as well as household level information on several observable characteristics such as consumption expenditure, income, caste and residence of the household (rural/urban) among others.

We referred to Chakraborty and Jayaraman (2019) to obtain the state wise implementation timeline of the mid day meal program. Using the timeline of implementation they provide, we obtained the number of years of potential exposure for each child covered in the IHDS survey, varying by his/her standard and state of residence. We dropped the states of Kerala, Gujarat, Puducherry, and Tamil Nadu from our analysis since they implemented the mid day meal scheme before the Supreme Court of India mandate. Additionally, we do not have information on when the mid day meal scheme was introduced in Jharkhand and Nagaland, and hence we opt these two states out of our analysis. For more details about program implementation, refer to Table A33 of Appendix D.

3.3 Methodology

The main objective of the study is to determine the causal impact of exposure to the mid day meal program on parental investment in their child's education related expenditures. We will look at the Intention-to-Treat estimates, where a child is defined as "treated" if he/she is in the relevant primary school grade to receive the mid day meal in a state that has implemented the program, irrespective of the type of school that he/she attends. The rationale behind defining treatment in this manner is that we suspect parents might transfer their children to government schools since they would want their children to receive the mid day meal program.

We define exposure to the mid day meal program both at the intensive and extensive margin. Exposure at the intensive margin is defined as the number of years that the individual was exposed to the mid day meal program based on his/her grade and the state that he/she belongs to (Refer to Table 3.1 for more details on how exposure is defined at the intensive margin). On the other hand, exposure at the extensive margin is a binary variable that takes a value of 1 if the individual was exposed to the mid day meal for at least a year, and 0 otherwise. For our main results, we use the definition of exposure at the extensive margin, but we will show that the results are both qualitatively and quantitatively similar even when we define exposure at the intensive margin.

Our sample consists of children who are currently attending school and are below 18 years of age, with the main unit of analysis being an individual child.

We use the following econometric specification to examine the causal impact of exposure to mid day meal program on parental investment in education related expenditures:

$$\ln(\mathrm{Y_{ihs}}) = \alpha_0 + \alpha_1 \mathrm{Exposure_{ihs}} + \alpha_2 \mathrm{W_i} + \alpha_3 \mathrm{H_h} + \phi_s + \varepsilon_{p(s)} \qquad (3.1)$$

where $\mathrm{Y_{ihs}}$ denotes the amount of educational expenditure for child *i* in household *h* in state *s*; $\mathrm{Exposure_{ihs}}$ is a dummy variable that takes a value of 1 if child 'i' in household 'h' in state 's' was exposed to the mid day meal program for at least one year, and 0 otherwise; $\mathrm{W_i}$ are child specific controls such as gender, dummy for child of household head, education level of parents, and also includes, age, standard, and birth order fixed effects; $\mathrm{H_h}$ includes household level characteristics such as religion, caste, log income, number of children in the household, number of persons in household, place of residence of household (rural/urban), and log of total educational expenditures; ϕ_s denotes state fixed effects; and finally errors are clustered at the primary sampling unit (PSU) level, which was a code for the village or neighbourhood the household was located

in. Our main dependent variables are the logarithm of the amount of educational expenditure in (i) school fees and (ii) books, uniform, and transport, and our main coefficient of interest is α_1.

Table 3.1: Years of Exposure by Grade and Year of Implementation

Grade in 2005	Year of Implementation			
	2002	2003	2004	2005
1	0	0	0	0
2	1	1	1	0
3	2	2	1	0
4	3	2	1	0
5	3	2	1	0
6	3	2	1	0
7	2	1	0	0
8	1	0	0	0
>9	0	0	0	0

Notes: The states of Jammu & Kashmir, Bihar, Assam, and West Bengal implemented the mid day meal program in 2005. Therefore, children in these states were exposed to the mid day meal program for less than a year when the survey was conducted. The mid day meal program was not implemented in the states of Chandigarh, Delhi, Mizoram, and Goa by 2005.

Our treatment variable $\text{Exposure}_{\text{ihs}}$ varies at the state and standard level, i.e. whether or not a child is exposed to the program depends on his/her state of residence and the standard the child was in during the 2005-06 IHDS survey. Since treatment depends on both state and standard, we introduce state and standard fixed effects in our model to ensure that we account for any time invariant unobserved characteristic of states and different standards. In addition, we control for birth order fixed effects and age fixed effects since it is possible that parental investment decisions depend on birth order and/or age of child.

We argue that given the state-wise staggered implementation of the mid day meal program for specific cohorts, access to this program was plausibly exogenous for households. In order to alleviate the concern that households might relocate to states where the program was running in order to gain access to the

program, we show that our results are robust to excluding those from our sample who have been living in their current place of residence for less than 3 years.

We also use a household fixed effects model and show that our results are robust to this alternative specification. In the household fixed effects specification, however, households in states where the mid day meal program was implemented in 2005 or after do not contribute to the analysis since there is no variation in exposure to mid day meal program across children in these households.

3.4 Results

Impact of Mid Day Meal Program on Education Related Expenditure

For our main results, we consider our primary outcome variables of interest, i.e. expenditure on school fees, and miscellaneous items such as books, uniform and transportation. Using the specification in eq. (3.1), exposure to the mid day meal program reduces spending on school fees by 16 percent (= ($e^{-0.177}$ -1)*100) (Column (2) of Table 3.2), and this is statistically significant at the 1 percent level, while there is no perceptible impact on expenditure on books, uniform, and transportation (Table 3.2). However, this is purely an Intention-to-Treat estimate since the mid day meal program is eligible only for children in primary education in government or government aided schools.

According to the 2009 Right to Education Act, education was made free for all children in India in the age bracket of 6 to 14 years old. But in 2005-06, parents of children attending primary schools still had to pay school fees. Nevertheless, the amount of school fees was significantly lower for government or public schools, as compared to private schools (Muralidharan and Kremer, 2006). Thus, the reduction in school fees that we observe might be a result of parents transferring their children from private to government schools, and

Table 3.2: Impact of Mid Day Meal Program on Educational Expenditure

Dependent variable	School Fees		Books, Uniform, and Others	
	(1)	(2)	(3)	(4)
Exposure	-0.106***	-0.177***	0.013	0.010
	(0.034)	(0.027)	(0.014)	(0.013)
Child is female	-0.175***	-0.167***	-0.046**	-0.052***
	(0.013)	(0.013)	(0.006)	(0.006)
Father's education	0.010***	0.007***	-0.007***	-0.003***
	(0.002)	(0.002)	(0.001)	(0.001)
Mother's education	0.004	0.016***	0.002*	-0.001
	(0.003)	(0.002)	(0.001)	(0.001)
Log(income of household)	0.090***	0.102***	0.011**	-0.003
	(0.013)	(0.011)	(0.006)	(0.005)
Observations	31,102	31,102	35,223	35,223
R-squared	0.680	0.712	0.777	0.793
State Fixed Effects	No	Yes	No	Yes

Note: The dependent variables are the logarithm of the amount of educational expenditures on each child in a given household. "Exposure" takes a value of 1 if the child was exposed to the mid day meal program for at least a year, and 0 otherwise. "Father's education" and "mother's education" are measured in terms of number of years of schooling. We also control for age, standard, and birth order fixed effects, dummy for child of household head and religion, caste, place of residence, number of members in household, number of children in household, and logarithm of total education expenditures of household. Standard errors clustered at the PSU level are given in parentheses. ***, **, and * denote statistical significance at 1, 5, and 10 percent levels, respectively.

therefore we explore this possibility in the next subsection.

Does Government School Enrollment Increase in Response to the Mid Day Meal Program?

To check if government school enrollment indeed increases in response to the mid day meal program, we test the following econometric specification:

$$G_{ihs} = \beta_0 + \beta_1 \text{Exposure}_{ihs} + \beta_2 W_i + \beta_3 H_h + \phi_s + \varepsilon_{p(s)} \tag{3.2}$$

where G_{ihs} is a dummy variable that takes a value of 1 if child 'i' in household 'h' in state 's' attends a government school, and 0 otherwise. Based on results

in column (1) of Table 3.3, the likelihood of attending government school increases by 4.4 percentage points in response to the mid day meal program, and this is statistically significant at the 1 percent level. Now, this higher probability might be a result of either increased enrollment of out of school children in government schools or due to a transfer of children from private schools to government schools. We are unable to explore the possibility of new enrollment going up with the data we have. However, we are able to explore the possibility of transfer of children from private to government schools.

In column 2 of Table 3.3, we see that enrollment in private schools goes down by 3.2 percentage points; therefore, we have suggestive evidence that a large proportion of the increase in enrollment in government schools might be a result of parents transferring their children from private schools to government schools with the desire to receive the mid day meal. While the probability of attending a government school is significantly negatively correlated with the education level of parents and income level of the household, the likelihood of attending a private school is increasing in the education level of parents and income of household. Nevertheless, a transfer from a private school to a government school or the increased likelihood of attending government schools might have unintended consequences on child learning and health outcomes. More specifically, the quality of teaching and learning outcomes appears to be better in private schools as compared to government schools (Singh and Sarkar, 2012). Hence, if the mid day meal program results in increased enrollment in government schools, the learning outcomes of primary school going children might be adversely affected if indeed, government schools are of poorer quality.

Table 3.3: Do Parents Transfer their Children to Government Schools to Receive Mid Day Meal?

Dependent variable	Government School (1)	Private School (2)
Exposure	0.044***	-0.032***
	(0.009)	(0.009)
Child is female	0.038***	-0.039***
	(0.004)	(0.004)
Father's education	-0.003***	0.003***
	(0.001)	(0.001)
Mother's education	-0.004***	0.002**
	(0.001)	(0.001)
Log(income of household)	-0.024***	0.024***
	(0.004)	(0.004)
Distance to school	-0.011***	0.005***
	(0.001)	(0.001)
Observations	36,108	36,108
R-squared	0.415	0.372

Note: The dependent variables are binary variables that take a value of 1 if the child attends the respective school type, and 0 otherwise. "Exposure" takes a value of 1 if the child was exposed to the mid day meal program for at least a year, and 0 otherwise. "Father's education" and "mother's education" are measured in terms of number of years of schooling. We also control for age, standard, birth order fixed effects, dummy for child of household head and religion, caste, place of residence, number of children in household, number of members in household, distance to school and state fixed effects. Standard errors clustered at the PSU level are given in parentheses. ***, **, and * denote statistical significance at 1, 5, and 10 percent levels, respectively.

Impact of Increased Government School Enrollment on Child Outcomes

Next, we study the impact of increased enrollment in government schools in response to the mid day meal program on child learning and health outcomes. Here, all the learning and health outcome variables are normalized relative to control mean and standard deviation. The IHDS survey asked a standardized set of questions on reading, writing, and mathematics to children aged between 8 and 11 years old. To study the impact of the increased enrollment in government

schools in response to the mid day meal program on learning outcomes (measured by reading, writing, and mathematics scores) and health outcomes, we use an instrumental variable estimation strategy, where we instrument enrollment in government schools by exposure to the mid day meal program. Table 3.3 provides the first stage results and we find that exposure to the mid day meal program is a strong predictor of whether a child attends a government school. In the second stage, we run the following econometric specification:

$$T_{ihs} = \gamma_0 + \gamma_1 G_{ihs} + \gamma_4 W_i + \gamma_5 H_h + \phi_s + \varepsilon_{p(s)} \tag{3.3}$$

where T_{ihs} measures the learning and health outcomes; G_{ihs} is a dummy variable that takes a value of 1 if child 'i' in household 'h' in state 's' attends a government school, and 0 otherwise. Our main coefficient of interest here is γ_1, and we instrument G_{ihs} by $Exposure_{ihs}$. From Table 3.4, we see that learning outcomes were not impacted by increased government school enrollment. While one of the objectives of the mid day meal program was to improve learning outcomes, increased enrollment in government schools failed to achieve the desired goal.

We also consider the impact on the health outcomes of the affected cohort in Table 3.5. We do not find evidence of any impact on the anthropometric measures such as height for age and weight for age. This could perhaps be attributed to the fact that exposure lasted for a relatively short time period - a maximum of three years when survey was conducted and anthropometric impacts may only be realised over a longer time frame.

Is There Gender Discrimination in Educational Expenditures?

Next, we study if there is any gender discrimination in educational expenditures and how such discrimination, if it exists, might affect the learning and health outcomes of the girl child.

Table 3.4: Impact of Mid Day Meal Exposure on Learning Outcomes

Dependent variable	Reading Score (1)	Math Score (2)	Writing Score (3)
Government School	2.985	-3.949	1.108
	(4.658)	(4.391)	(3.669)
Child is female	-0.221	0.063	-0.116
	(0.230)	(0.218)	(0.185)
Father's education	0.052	-0.024	0.030
	(0.051)	(0.048)	(0.040)
Mother's education	0.063	-0.029	0.034
	(0.064)	(0.060)	(0.050)
Log(income of household)	0.249	-0.166	0.093
	(0.294)	(0.279)	(0.233)
Observations	9,045	9,013	8,971

Note: The results are for the sub-sample of students who are aged between 8 and 11 years old and are in standard 1 to standard 7. All the learning outcomes are standardized relative to control mean and standard deviation. The above estimates are from instrumental variable estimation where "Government School"is instrumented for by exposure to the mid day meal program. Exposure to the mid day meal program takes a value of 1 if the child was exposed to the mid day meal program for at least a year, and 0 otherwise. "Father's education" and "mother's education" are measured in terms of number of years of schooling. We also control for age, standard, birth order fixed effects, dummy for child of household head and religion, caste, place of residence, number of members in household, number of children in household and state fixed effects. Standard errors clustered at the PSU level are given in parentheses. ***, **, and * denote statistical significance at 1, 5, and 10 percent levels, respectively.

$$\begin{aligned}\ln(\mathrm{Y_{ihs}}) = \delta_0 + \delta_1 \mathrm{Exposure_{ihs}} + \delta_2 \mathrm{MaleProp_{ihs}} + \delta_3 \mathrm{SiblingsNo_{ihs}} \\ + \delta_4(\mathrm{Exposure_{ihs}} \times \mathrm{MaleProp_{ihs}}) + \delta_5 \mathrm{W_i} + \delta_6 \mathrm{H_h} \\ + \phi_s + \varepsilon_{p(s)} \qquad (3.4)\end{aligned}$$

where $\mathrm{Y_{ihs}}$ denotes the amount of educational expenditure for girl *i* in household *h* in state *s*; $\mathrm{MaleProp_{ihs}}$ denotes the proportion of male siblings a girl child has;

Table 3.5: Impact of Mid Day Meal Exposure on Health Outcomes

Dependent variable	Height for Age (1)	Weight for Age (2)
Government School	1.984	2.564
	(1.935)	(2.925)
Child is female	-0.120	-0.176
	(0.106)	(0.159)
Father's education	0.022	0.028
	(0.021)	(0.031)
Mother's education	0.030	0.038
	(0.028)	(0.043)
Log(Income) of household	0.126	0.189
	(0.109)	(0.167)
Observations	12,479	12,479

Note: The dependent variables "height for age" and "weight for age" are both standardized relative to control mean and standard deviation. The above estimates are from instrumental variable estimation where "Government School"is instrumented for by exposure to the mid day meal program. Exposure to the mid day meal program takes a value of 1 if the child was exposed to the mid day meal program for at least a year, and 0 otherwise. "Father's education" and "mother's education" are measured in terms of number of years of schooling. We also control for age, standard, birth order fixed effects, dummy for child of household head and religion, caste, place of residence, number of members in household, number of children in household and state fixed effects. Standard errors clustered at the PSU level are given in parentheses. ***, **, and * denote statistical significance at 1, 5, and 10 percent levels, respectively.

and, $\text{SiblingsNo}_{\text{ihs}}$ is the number of siblings that each girl child has. Here, we restrict our sample to female children. Our main coefficient of interest here is δ_4, which identifies the impact of having a higher proportion of male siblings on educational expenditures of a girl child. Our hypothesis is that if gender discrimination exists, female children would be further negatively impacted if they have a higher proportion of male siblings. Based on the interaction term in Table 3.6, we do not find evidence of any gender discrimination in educational expenditures that might disadvantage the girl child.

Table 3.6: Is There Gender Discrimination in Educational Expenditures?

Dependent Variable	Child is male		Child is female	
	School Fees (1)	Others (2)	School Fees (3)	Others (4)
Exposure × Prop. of male siblings	-0.019**	-0.008	0.010	0.004
	(0.009)	(0.006)	(0.010)	(0.006)
Exposure	-0.045***	-0.011*	-0.045***	-0.009
	(0.010)	(0.006)	(0.011)	(0.007)
Prop. of male siblings	-0.033***	-0.013***	-0.032***	-0.018***
	(0.006)	(0.004)	(0.006)	(0.004)
Number of siblings	-0.104***	-0.108***	-0.102***	-0.102***
	(0.003)	(0.002)	(0.003)	(0.002)
Father's education	-0.001	-0.000	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Mother's education	0.000	0.001*	0.003***	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)
Log(income of household)	-0.006***	-0.004***	-0.006***	-0.004***
	(0.002)	(0.001)	(0.002)	(0.001)
Observations	13,729	13,729	12,223	12,223
R-squared	0.260	0.436	0.276	0.438
State Fixed Effects	Yes	Yes	Yes	Yes

Note: 'Others' includes books, uniform, and transportation. "Exposure" takes a value of 1 if the child was exposed to the mid day meal program for at least a year, and 0 otherwise. "Father's education" and "mother's education" are measured in terms of number of years of schooling. We also control for age, standard, and birth order fixed effects, dummy for child of household head and religion, caste, place of residence, number of members in household, number of children in household, logarithm of total education expenditures of household and state fixed effects. Standard errors clustered at the PSU code level are given in parentheses. ***, **, and * denote statistical significance at 1, 5, and 10 percent levels, respectively.

Do Parents Have Greater Confidence in Government Schools?

The household section of the IHDS survey asks respondents to report their faith in different institutions such as the military, politicians, state government, hospitals, and schools. In this section we aim to answer the question of whether the provision of mid day meal increases the confidence of households in government schools. On one hand, provision of a free meal could increase the faith people have in government schools as they would value improved nutrition for their children. On the other hand, it is possible that they chose to transfer their children to government schools in response to the program and the learning outcomes of their children did not improve/worsened due to this transfer or their children were already in government schools but the implementation of

the program led to diversion of teaching inputs such as teachers' time away from teaching leading to worse learning outcomes. If so, parents would lose confidence in schools and their ability to impart quality education. Thus, it would be interesting to note how such a large scale school feeding program actually impacted the level of confidence parents have in government schools.

Since IHDS asks about the level of confidence parents have in schools in general and not government schools, we restrict our sample to households where parents have experience of government schools. To do so, we perform a subsample analysis at the household level and restrict our sample to households where at least one child attends a government school and no child attends a private school (Column (1) of Table A34 in Appendix D). This allows us to understand the level of confidence parents of government school going children have in government schools. Our assumption here is that the response to the question of confidence in schools is based on their experience of the school their child attends. Here, our main outcome variable of interest is Exposureany, which is a dummy variable that takes a value of 1 if there is at least one child in the household who is exposed to the mid day meal program, and 0 otherwise. Here, the main dependent variable is confidence which takes values 1-3 with 3 being great deal of confidence and 1 being hardly any confidence.

We find that confidence of households in government schools reduces in response to exposure to the mid day meal. This finding ties in with the result on no improvement in learning outcomes and indicates that even though a free meal was provided in schools, when there was no improvement in learning outcomes, either due to diversion of teaching inputs or overall lower quality of education in government schools, particularly experienced by transfer cases, parents lost confidence in government schools. Thus, we find that such a large school feeding program ended up undermining government schools instead of increasing support for them.

3.5 Robustness Checks

In this section, we perform a few robustness checks to lend validity to our main findings on the impact of mid day meal exposure on parental investment in education.

Household Fixed Effects

First, we use a household fixed effects specification to control for any unobserved time invariant heterogeneity between households. The results are shown in Table A35 in Appendix D. Here, identification is based on the variation in exposure to the program within a household. If there are any unobservable characteristics specific to a household that determine parental investments such as motivation, focus on child's education etc, we can capture that using household fixed effects. Using this specification, we find that exposure to the mid day meal program reduces school fees by 20 percent (= ($e^{-0.227}$ -1)*100), and this is similar to what we obtained in the state fixed effects specification (Column (2) of Table 3.2). Thus, our results are robust to this alternative specification.

Intensive Margin Effects

Next, we study the impact of mid day meal exposure at the intensive margin on educational expenditures. Since there was state wise variation in the implementation of the program, there were differences in years of exposure across cohorts. The year in which the program was first implemented in any state was 2002 and the IHDS-I survey was conducted in 2005. Thus, the number of years of exposure could vary from 0 to 3. Analysing the effect at the intensive margin (Table A36 in Appendix D), we find that the reduction in school fees is the largest when children are exposed to the program for two years. This could potentially be a result of more parents deciding to transfer their children to government schools in the year following the one when they were first exposed.

This could perhaps be due to the fact that most people would take some time to acknowledge and internalise the benefits of such a program and make the decision to move their child to a government school. And once they do make the decision, it is more likely that they would wait for the school year to finish before they transfer them.

Inter-state Migration

Since we are exploiting state wise variation in the implementation of the mid day meal program, inter-state migration might have a confounding effect and bias our impact estimates. In order to address this concern, we restrict our analysis to households who have lived in the current place of residence for at least three years. We chose to restrict by three years since the maximum possible exposure to the program is three years. As seen from Column (1) of Table A37 in Appendix D, the amount of expenditure on school fees reduces by 16 percent, which is similar to the point estimates that we obtained from the full sample. Therefore, the possibility of contamination of treatment due to inter-state migration can be ruled out.

Clustering at State Level

We also verify the robustness of our results to clustering at different levels. In the analysis so far, we clustered at the PSU level. Now, we cluster standard errors for the same specification at the state level. The results are presented in Table A38 in Appendix D and show that our results are robust to this alternative specification.

Placebo Test

To further validate our results, we conduct a placebo test where we restrict our sample to children who did not receive the mid day meal program. Further,

we restrict the sample to states where the mid day meal program was not implemented and define children who are attending grades 1 to 5 in these states as 'treated', and children attending grades 6 to 12 as the comparison group. We should not expect to see any statistically significant treatment effect in this specification since the children who are defined as 'treated' belong to states where the mid day meal program was not implemented and would not have been beneficiaries of the scheme. As seen from Table A39 in Appendix D, we do not find any treatment effect which lends validity to our main results.

3.6 Heterogeneity Analysis

Restricting all the coefficient estimates to be similar across the entire sample does not allow us to identify any impact heterogeneity that may exist. For example, the specification in eq. (3.1) masks any treatment heterogeneity across different consumption quartiles or place of residence (rural/urban). We therefore explore the impact heterogeneity along these two dimensions.

Consumption level

Since consumption is non-negative and is less subject to seasonal fluctuations, we used consumption as a proxy for economic well-being. We then divided our households into four different quartiles based on consumption per capita (Table 3.7).

While expenditure declines in all four consumption quartiles, we find that the decline is strongest in the second quartile, followed by first and third quartile. Since the poorest are more likely to be enrolled in government schools already, we might not see the strongest impact on them.[26] On the other hand, the richest are less likely to respond to the provision of a free meal. Hence, the ones most likely to respond could perhaps be those in the middle of the con-

[26]The proportion of children enrolled in government schools are as follows: 84.92%, 73.67%, 61.38% and 40.65% in the first, second, third, and fourth quartiles respectively.

sumption spectrum. Perhaps, this explains why we see the strongest decline for those in the second quartile. This result can be further validated by Table A40 in Appendix D, where we consider the likelihood of being enrolled in government/ private school across consumption quartiles. We find that the likelihood of being enrolled in government schools closely tracks the pattern we see in Table 3.7 with the greatest increase visible in the second quartile. We can see some suggestive evidence of parents transferring their children from private schools to government schools from Columns (5) to (8) of Table A40 since the decrease in likelihood of attending private school is also greatest for the second quartile. This, along with the fact that households in the second quartile experienced the largest drop in school fees, suggests that parents might have transferred their children from private schools to government schools in response to the mid day meal program, with the strongest impacts among those in the middle of consumption distribution.

Type of Residence

Next, we study treatment heterogeneity between rural and urban households. Rural households experienced a sharper decline in school fees compared to urban households due to exposure to the mid day meal program (Table A41 in Appendix D). While there was a fall in private school enrollment in both rural and urban areas, the decline was much larger in rural areas and the difference is statistically significant (Table A42 in Appendix D).

Thus, it appears those in rural areas responded more to the mid day meal program, possibly because they were poorer and one free meal mattered more to them compared to those in urban areas.[27]

[27]Based on IHDS I data, the average per capita annual income of a rural household was Rs 7118 compared to Rs 14079 of an urban household.

Table 3.7: Impact Heterogeneity by Consumption Level

Dependent variable	School Fees			
	1st Quartile	2nd Quartile	3rd Quartile	4th Quartile
	(1)	(2)	(3)	(4)
Exposure	-0.291***	-0.366***	-0.281***	-0.217***
	(0.029)	(0.030)	(0.030)	(0.029)
Child is female	-0.185***	-0.155***	-0.183***	-0.132***
	(0.024)	(0.026)	(0.024)	(0.022)
Father's education	0.007*	0.010*	0.007*	0.008*
	(0.004)	(0.004)	(0.004)	(0.004)
Mother's education	0.016***	0.012***	0.014**	0.022***
	(0.006)	(0.005)	(0.004)	(0.004)
	$P(Sch_1 = Sch_2 = Sch_3 = Sch_4) = 0.004$			
Observations	7,786	7,963	8,163	7,613

Note: Each of the columns represents different consumption quartiles with quartile 1 comprising of households with the least consumption per capita and quartile 4 comprising of households with the highest consumption per capita. The dependent variables are the logarithm of the amount of educational expenditures on each child in a given household. "Exposure" takes a value of 1 if the child was exposed to the mid day meal program for at least a year, and 0 otherwise. "Father's education" and "mother's education" are measured in terms of number of years of schooling. We also control for age, standard, and birth order fixed effects, dummy for child of household head and religion, caste, place of residence, number of members in household, number of children in household, logarithm of total education expenditures of household and state fixed effects. The p-values for the joint test of equality of the coefficients across different quartiles using seemingly unrelated regressions are given in the middle panel. Standard errors clustered at the PSU level are given in parentheses. ***, **, and * denote statistical significance at 1, 5, and 10 percent levels, respectively.

3.7 Conclusion

In this paper, we have tried to explore how parents make educational investment decisions for their children in response to government benefit programs. In this particular context, we studied the mid day meal program in India, which is the world's largest school feeding program. The staggered implementation of the scheme, which is arguably exogenous, across different states allows us to draw causal inference on the impact of this provision on how parents make educational investment decisions. Using a state fixed effects specification and

controlling for various child and household level characteristics, we find that exposure to the mid day meal program reduces expenditure on school fees by 16 percent, which is a result of higher enrollment in government schools. We find suggestive evidence that this higher enrollment, in part, is caused by parents moving their children from private schools to government schools. Our results are robust to alternative specifications such as using household fixed effects, clustering standard errors at different levels and addressing potential concerns regarding inter-state migration.

We further study the impact of higher enrollment in government schools on learning and health outcomes. We look at reading, writing, and mathematics scores and do not find any improvement in the learning outcomes. The mid day meal program also does not lead to better health outcomes, and this could partly be because we are looking at a relatively short time frame (with a maximum exposure of three years), and anthropometric measures such as weight for age and height for age might take time to respond to the mid day meal provision. We also do not find evidence of any gender discrimination in how parents make educational expenditures in response to the mid day meal program. And, thus the learning and health outcomes do not differ between boys and girls.

The results are very interesting from a policy perspective. The Ministry of Education under the Government of India initiated the mid day meal program with the objective of providing quality food to primary school students, especially those from disadvantaged backgrounds, and to improve school attendance and ultimately, learning and health outcomes of children. However, the resulting increased enrollment in government schools, possibly due to transfer from private schools did not result in any improvement in learning outcomes. On one hand, this could be simply because children who transferred to government schools now were not experiencing a higher quality of education. It is also possible that within government schools, the program resulted in diversion of teaching inputs such as teachers' time. Finally, it is also possible that due to

transfer of students from private to government schools, there was an unanticipated rise in class sizes. Any of the above factors, individually or in combination could explain our results.

From a policy perspective, it is important to be aware of the unintended ramifications that such a school feeding program could have. While the policy was very well-intentioned and may have some positive impacts on children in the long run, our shorter term results highlight the need to proceed with caution. Future studies can therefore explore the factors for the lack of improvement in learning outcomes for children who are exposed to the mid day meal program in government schools.

4 Singapore as a Sustainable City: Past, Present, and the Future[28]

4.1 Introduction

Singapore has achieved impressive economic growth over the last half a century. The GDP per capita was only around US$4,088 in constant 2010 USD in 1965 when Singapore became independent, but it reached US$58,248 in 2018, according to the World Development Indicators. As Singapore became more prosperous, it has increasingly become a destination that foreigners wish to migrate to. Correspondingly, the total population of Singapore almost tripled from around 1.9 million to 5.6 million between 1965 and 2017. During this massive economic transformation from a developing country to a country that is among the richest, Singapore faced various issues that challenged its sustainability and liveability. In this paper, we provide an overview of the major sustainability challenges Singapore has experienced and policies that have been adopted to address them, particularly in the areas of land use, transportation, waste management, water, and energy. We argue that Singapore has been successful in addressing these challenges owing to the sound long-term vision and planning as well as flexibility in the implementation of policies to tackle them. At the end of this paper, we provide some discussion on policy options, challenges, and opportunities for making Singapore more sustainable and liveable.

4.2 Coping with Land Scarcity

Land scarcity has been recognised as one of the most serious challenges by the leaders of Singapore since its independence. Therefore, efficient land use with sound planning has been among the most important policy objectives to

[28]This paper has been co-authored with Professor Tomoki Fujii (Singapore Management University). We thank Oscar Bian Ce for research assistance. We also thank Euston Quah, Surabhi Mohan, Phang Sock-Yong, and Yue Lee Lian for their comments. All mistakes remain ours.

enable sustainable growth in Singapore. Efficient land use was promoted by the government, empowered by the Land Acquisition Act of 1966 and subsequent amendments, which enabled the government to compulsorily acquire land from private landowners at below-market prices for public and certain other purposes (Phang et al., 2018). The government indeed aggressively acquired land to build public housing and transportation infrastructure. By 1985, the government became the biggest land owner by far, owning 76.2 percent of Singapore (Tortajada and Biswas, 2017).

Singapore's push towards efficient land use has been supported by sound planning with a long-term vision, starting from the first Concept Plan developed in 1971. The Concept Plan 1971 laid the foundation for the growth of a young nation by advocating the development of a ring structure of satellite towns through the creation of new housing towns, industrial estates, recreational spaces, and an efficient transport infrastructure around a centrally located water body. The Concept Plan 1971 is considered instrumental in shaping the structure of Singapore and guiding its development over time (Urban Redevelopment Authority, 2019). Since then, the Concept Plan was revised three times in 1991, 2001, and 2011 to respond to the changing needs. These revisions involved the whole government and long-term land use decisions were taken collectively in government (Ng, 2017).

The Concept Plan 1991 shifted the focus from meeting basic needs towards achieving more balanced and inclusive growth. The plan proposed decentralisation of commercial and industrial centres and creation of technological corridors, made up of academic institutions and business parks, to facilitate exchange of ideas and innovation. With the vision to become a thriving world class city in the 21st century, the Concept Plan 2001 proposed various housing locations and types to meet different lifestyles, increase green spaces, and explored opportunities to transform Singapore into a global financial hub. The latest review of the Concept Plan in 2011-2013 led to the release of the Land Use Plan 2030 by

the Ministry of National Development, which outlines the strategies to provide a high quality living environment for all Singaporeans. They include providing good affordable homes with a full range of amenities, integrating greenery into the environment, providing greater mobility with enhanced transport connectivity, sustaining a vibrant economy with good jobs, and ensuring room for growth and a good living environment in future. Thus the gradual evolution of the Concept Plan through the years demonstrates the fact that Singapore has been able to keep pace with the needs of time and offer its residents a wide range of resources.

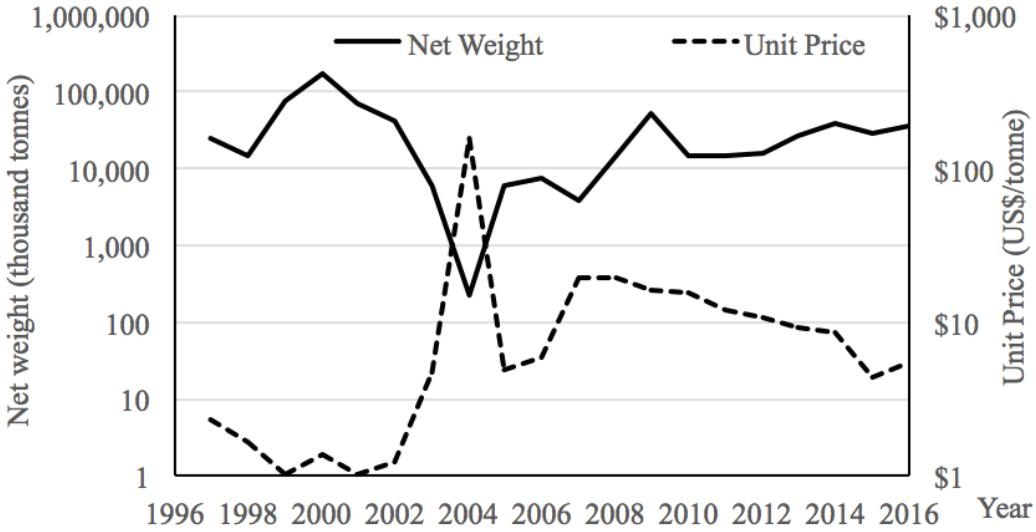
With the land use planning outlined in the Concept Plan, Singapore has approached the land scarcity issue through three types of approaches. First, Singapore has directly increased land supply through reclamation. Second, Singapore has promoted vertical urbanism to address the competing needs for land in housing, transport, and commerce. Third, as the evolution of the Concept Plan above indicates, Singapore has increasingly shifted its focus of land policy towards sustainability and liveability by exploring opportunities to promote eco-friendly buildings and eco-smart lifestyles and to foster community spirit. Below, we study in detail each of these approaches.

Horizontal Expansion through Land Reclamation

Land reclamation projects have been at the heart of Singapore's land policy to provide housing, commercial, and industrial space. Through land reclamation, Singapore has expanded its total land area from 580 square kilometres in 1965 to 721 square kilometres today. The government has a target to further expand the land area to 780 square kilometres by the end of 2030.

The first land reclamation in Singapore took place in present-day Boat Quay in 1822 when the British had colonised the island. Many of Singapore's notable buildings today, including those in the Marina Bay Financial Centre and

Figure 4.1: Net Weight of Sand Import and Average Unit Price in Singapore



Note: Based on the United Nations COMTRADE statistics using HS 1996 classification and code 2505 (“natural sand except sand for mineral extraction")

the Changi Airport, have all been constructed on reclaimed land. Among the most prominent land reclamation projects is the East Coast Reclamation, popularly known as the Great Reclamation, which added a total area of 15.25 square kilometres along the southeastern part of the island, mostly for commercial and residential purposes. Jurong Island, which is home to many petrochemical firms today, was created by reclaiming the sea around seven islands and amalgamating them. Other notable reclamation projects include those in Telok Ayer, Kallang Basin, and Beach Road.

Most of the sand for reclamation used to be imported from the neighbouring countries of Malaysia and Indonesia. However, there was an official ban on sand exports by Malaysia in 1997 and by Indonesia in 2007, following which Singapore was compelled to look for alternative source countries such as Cambodia, Vietnam, the Philippines, and Myanmar. However, Vietnam banned sand exports to Singapore in 2009. In 2017, Cambodia too declared a complete ban on sand exports to Singapore (BBC, 2017). Nevertheless, these bans do not appear to be fully enforced and Singapore continues to import from these coun-

tries (Banergee, 2018). Indeed, Singapore has been accused of allowing illegal sand import. While Singapore denies such an allegation, there is a discrepancy between the quantity of sand imports reported by Singapore and the quantity of sand exports reported by the source countries. For example, Singapore reported 73.6 million tonnes in sand imports from Cambodia since 2007, but the Cambodian government reported that only 2.7 million tonnes left for Singapore (Siau, 2017).

Besides the concerns for environmental degradation due to illegal sand exports from source countries, Singapore's massive land reclamation has also made neighbouring countries, such as Indonesia, wary that it may lead to a loss of its own sovereign territory (Subramanian, 2017). Furthermore, land reclamation became more expensive. The average import price of sand skyrocketed from around US$ 1 per tonne in 1999 to over $150 per tonne in 2004. Even though the recent price trend is downward, the price remained well above US$5 (Figure 4.1). All these points raise the importance of reducing the dependency on imported sand for reclamation.

As a result, empoldering – a method of reclamation in which a dike is first built around the area to be reclaimed and then the water inside is drained – was considered, because it can significantly limit the potential damage to the surrounding coastal and marine ecosystem. Also, compared to the traditional method of infilling with sand, empoldering requires less sand and saves on upfront construction costs (Yeo, 2015). The Housing Development Board (HDB) – a government organisation that provides public housing in Singapore – adopted empoldering for the ongoing reclamation of Pulau Tekong.

Though efforts to increase the land area through reclamation has clearly helped mitigate the space constraint that Singapore faces, horizontal expansion alone is unlikely to resolve all the land issues, because reclamation is already expensive and takes a long time to complete. Furthermore, land reclamation will continue to become more expensive, even if the import sand price remains

stable. This is because the sites suitable for land reclamation become deeper and deeper into the sea as Singapore's land reclamation expands. We, therefore, turn to vertical urbanism as a complementary approach to address land scarcity in Singapore.

Growing Taller: Vertical Urbanism in Singapore

Competing needs for land between housing, transport, and commercial uses necessitated Singapore to turn to the concept of vertical urbanism. Vertical growth is an apparent solution to the problems of land scarcity and urban sprawl, and it may lessen environmental damage (Wong, 2004). Singapore has promoted vertical urbanism through various policies such as relaxed storey height limits and facilitation of collective sales (Phang et al., 2018), the latter of which would lead to increased supply of units. Through vertical urbanism, various needs for space can be simultaneously fulfilled and open space for greenery can be created. Tall buildings can also significantly lessen the volume of traffic and reduce carbon footprint, if suitable policies are in place.

Singapore's history of vertical urbanism will be incomplete without understanding the critical role that the HDB played in the housing market. The HDB was founded in 1960 – when many people were living in unhygienic slums and crowded squatter settlements – and tasked to solve Singapore's housing crisis (Housing Development Board, 2017). The HDB buildings in early years were made of slab blocks with 10 storeys or fewer. However, in the 1970s and 1980s, as the HDBs' supply began to expand, a majority of the HDB buildings had more than 10 storeys. In the 1990s, 30-storey HDB complexes appeared, and the first 40-storey complex was completed in Toa Payoh in 2005. HDB buildings and private condominiums with 30 or even 40 storeys are now common in Singapore. The tallest HDB in Singapore currently is the 50-storey Pinnacle@Duxton in Duxton Plain completed in 2009 with 1848 units (Lee, 2011).

HDB buildings are clustered in a town and normally have essential facilities such as supermarkets, hawker centres, clinics, schools, and recreational facilities in their vicinity. Today, 81 percent of Singaporeans live in a HDB unit, typically in a high-rise building, and about 90 percent of them own the unit they occupy.

While constructing more such high-rise, high density residential buildings, it was essential for policymakers to understand the attitude of the residents towards vertical urbanism. Wong (2004) interviewed residents of newly constructed tall buildings and found certain pull and push factors that, respectively, attract and repel residents. According to the survey results, good view, fresher air, ventilation, and better quality of housing were taken as some of the benefits of vertical urbanism. On the other hand, perceived drawbacks included safety issues, long waiting time for lifts, lack of community interaction, high-rise littering, and high prices of high-floor units.

In recent decades, as the policy focus shifts towards sustainability and liveability, the possibility of exploiting the rooftops of high-rises as gardens has been explored. Greenery can be extended skywards, such that it is closer to individual homes in tall buildings and fosters interactions within the community. Rooftop greenery can be beneficial not only from an aesthetic viewpoint but also from the perspective of rainwater harvesting and energy conservation through the better insulation greenery provides. Various programs have been put in place to promote skyrise greenery in Singapore. For example, the Urban Redevelopment Authority (URA) launched the Landscaping for Urban Space and High-Rises (LUSH) in 2009 to incentivise developers to build sky terraces and roof gardens in new constructions. The Skyrise Greenery Incentive Scheme, which subsidises installation of skyrise greenery in existing buildings, was also initiated as part of the Singapore Blueprint 2009. However, one of the primary concerns for developers has been that rooftop greenery tends to be underutilised and people have a natural inclination to go to parks at the ground level (Yuen

and Hien, 2005).

While growing taller has been the primary focus of vertical urbanism in Singapore, Singapore also uses its underground space for various purposes such as shops, carparks, rail network, roads, caverns, underground pedestrian networks, and utility tunnels. Underground space is relatively expensive to develop but it has some advantages over above-ground spaces such as insulation from scorching sun and torrential rain in the tropical climate. Deep underground space can be used for storage, transport, utility, and industrial facilities. In view of this, Singapore is indeed exploring greater use of its underground space (Authority and ARUP, 2014).

Though critics of vertical urbanism argue that it leads to social segregation and disrupts the horizontal dynamism of urban space (Hou, 2012), in a land-constrained city like Singapore, vertical urbanism is among the most practical ways to provide residential and commercial space to cater to an increasing population.

Improving Land Use for Sustainable and Liveable Singapore

As environmental awareness of Singaporeans rises and as they increasingly require more than just a shelter, the emphasis of land policy has shifted towards the construction of more eco-friendly buildings and promotion of an eco-smart lifestyle. One example is the Elevator Energy Regeneration System in the lifts of HDB buildings. These lifts recover energy from the movement of elevators to power other common services and have already been installed in 350 blocks in Punggol. There are plans to expand this provision further to new and existing HDB blocks (Cheng and Tong, 2017). Another example is the use of LED lighting in common areas, which is more energy-efficient than the conventional lights. Other green measures include installation of solar panels in rooftops and centralised chutes as discussed below.

The government of Singapore has used a sound mix of normative messages and economic incentives over time to achieve desired economic and social outcomes. It has set an ambitious target of making 80 percent of its buildings 'green' by 2030. Some of the first initiatives towards greener buildings were taken in mid 2000s. For example, the Building and Construction Authority (BCA) Green Mark Scheme was launched in 2005, and the first Green Building Masterplan, which stimulated industry stakeholders to adopt new green buildings, was unveiled in 2006. The second Green Building Masterplan, which was launched in 2009 in partnership with the Inter-Ministerial Committee on Sustainable Development, focused on incorporating the public and private sectors in the drive towards achieving greenery as well as improving green building technology, imposing minimum standards, and raising general awareness among the population (Building and Construction Authority, 2009).

While the first two Green Building Masterplans focused on the roles of developers, designers, and builders to construct eco-friendly buildings through incentives such as the BCA Green Mark Scheme, the third Green Building Masterplan published in 2014 raised awareness among the occupants of these buildings about the adoption of eco-friendly ways of living. Under the third Masterplan, a $50 million Green Mark Incentive Scheme for Existing Building and Premises was introduced to promote environmental friendly retrofits through co-funding. In 2018, the BCA further launched a new voluntary rating, Green Mark for Super Low Energy Building (the best-in-class energy performing Green Mark Building that achieves at least 40% energy saving based on prevailing code, or 60% energy saving above 2005 building codes) and Zero Energy Building (the best-in-class energy performing Green Mark Building with all of its energy consumption including plug load, supplied from renewable source).

While the Green Mark Scheme is mostly a voluntary scheme, any building on the land sold under the Government Land Sales Programme in selected strategic areas is required to meet the prescribed Green Mark Certification. A good

example is Punggol Eco-Town, in which any building is required to achieve Green Mark Goldplus rating. Punggol Eco-Town now boasts of a sustainable waterfront town of the 21st century and is an exemplary model using energy- and resource-efficient solutions, including solar photovoltaic (PV) system, elevator energy reservation system, smart grids, and effective water management solutions through rainwater harvesting.

The measures discussed so far have been taken to address the sustainability issues in areas of land use, but the push towards greener buildings and lifestyles has also risen from the concomitant issue of liveability. Singapore has worked towards realising the “garden city" vision put forward by then Prime Minister Lee Kuan Yew in 1967 to enhance the attractiveness and liveability of the city. For example, Singapore has introduced regulatory provisions to mandate land within developments to contribute to the overall greenery of the city and set aside planting verges along roads (Tan, Puay Yok, 2017). Efforts have also been made to bring greenery and nature into the residential and commercial space to create a more liveable Singapore. Today, Singapore already tops the ranking of urban tree density (Tan, Audrey, 2017). The government now aims to have 9 in 10 homes within 10 minutes’ walk from a park and plans to build 400 kilometres of park connectors and 100 kilometres of waterways open to recreational activities by 2030 (National Parks, 2017).

There has also been a concerted effort to bring more greenery into living spaces and create better public spaces for the community. One noteworthy ongoing project is Tengah, popularly known as the ‘Forest Town’, which will feature car-free city centre, walking and cycling paths along all roads, and greenery woven through the town, from a large central park to community farmways that run through housing estates (Heng, 2016). Upon completion in about two decades, Tengah will have an estimated 42,000 new homes with public housing comprising a vast majority of 70 percent (Cheng, 2016). Besides, the URA is creating car-free zones on weekend and encouraging the provision of green spaces under

the LUSH program, as mentioned earlier.

Creating an active and vibrant community to enhance liveability has also become a focal point in Singapore's policy dialogue. Initiatives have been taken to make better use of public spaces – including playgrounds, hawker centres, void decks, and parks – for the civil community, where people can come together to exchange new ideas or just sit and relax. For example, the URA launched the 'Pick a Bench, Pick a Place' project in 2014, in which the public was invited to vote for their favourite bench design and location for the bench to be installed. In this project, 42 benches were installed across 15 locations in Singapore, and these benches provide the community with resting place and serve as focal points for community interactions (Urban Redevelopment Authority, 2014). Ongoing efforts to raise liveability also include research and development (R&D) programs. One prime example is the Land and Liveability National Innovation Challenge, a multi-agency effort that seeks to leverage research and development to come up with innovative solutions to increase Singapore's land capacity for its long-term development needs and to provide options for future generations (Foundation, 2018).

4.3 Building an Efficient Transportation System

Land-use policies work hand in hand with transportation policies, because where to live, where to work, and where to play can depend much on whether there is a good transportation system. A good transportation system is also crucial for the sustainable growth of a city as congestion undermines the smooth movement of goods and people within the city and reduces its attractiveness and the welfare of its residents. Therefore, the presence of an efficient transportation system is vital for both liveability and sustainability of a city. Indeed, building a good transportation system has always been of great importance in Singapore's public policy. Singapore has managed to pre-empt congestion and ensure smooth

traffic flow through careful long-term planning and flexible implementation of policies to address unexpected issues.

While Singapore already had a road network with a total of 800 kilometres of road length in the 1960s (Centre for Liveable Cities and Land Transport Authority, 2013), opening of new HDB towns and increasing population and industrial activities necessitated the construction of more roads. Therefore, Singapore has continued to add and improve roads, and there is a total of 3,500 kilometres of road in Singapore as of 2017 (Land Transport Authority, 2018). Besides this sizable growth in the total road length, Singapore opened 11 expressways with a total length of 164 kilometres since 1965, when there was no expressway. In 2012, roads constituted 12 percent of the total land area and adding roads further will be expensive in land-scarce Singapore. Indeed, just increasing the supply of roads has never been and will not be a fundamental solution to the challenges of meeting the increasing transportation demand in Singapore.

Singapore has taken a two-pronged approach to address transportation issues. One approach is to strengthen the push factors from private vehicle transportation to manage congestion by making the usage and ownership of private vehicles more expensive. The other approach is to address pull factors into alternative modes of transportation by improving the public transportation system. In this section, we review both approaches and explore future opportunities and challenges in Singapore's transportation system.

Past and Present Policies to Manage Traffic Congestion

While roads have been built across the island, demand-side management has played a critical role in the transportation policy of land-scarce Singapore. To address urban traffic congestion, the government has implemented, broadly speaking, two types of policies to manage demand. One type of policies is to disincentivise the use of cars during peak hours by imposing a charge. The other type

of policies attempts to reduce car ownership.

One of the first policies aimed at reducing the use of cars, the Area Licensing Scheme (ALS), was implemented in 1975, when a rapid increase in car ownership due to increasing incomes was leading to a major traffic congestion in the Central Business District. The ALS was the first comprehensive road pricing scheme ever implemented in the world (Rodriguez, 1976). Under the ALS, drivers of all vehicles excluding exempted vehicles such as buses, taxis, motorcycles, commercial vehicles, police and military vehicles, ambulances, fire engines, and high occupancy vehicles (HOVs) with at least four passengers had to pay an entry fee to enter the restricted zone (RZ) during the peak hours between 7.30 am and 9.30 am, except for Sundays and public holidays. The payment was made through the purchase of a paper license – priced initially at S$3 per day or S$60 per month – and it had to be displayed on the vehicle's windscreen. To support the ALS, the government also implemented complementary measures such as the hike of parking rates in the RZ and construction of roads that circumvent the RZ.

The ALS was generally deemed successful in curbing urban congestion and encouraging people to travel in public transport. For example, the share of public transportation users increased from 33 percent in the pre-ALS period to 69 percent in the post-ALS period (Phang and Toh, 1997). The average speed of traffic in the Central Business District during the peak hours was 19 kilometres per hour in 1975, but by May 1991, it had increased to 36 kilometres per hour (Phang and Toh, 1997). This figure compares favourably to the average downtown peak hour vehicular speed of 10 and 18 kilometres per hour in New York and London, respectively (Menon et al., 1993). Not only did the implementation of ALS improve the speed of traffic, but it also helped reduce air pollution in the CBD and earned the government a savings of at least US$ 500 million on road repairs and investment in infrastructure (Holland and Watson, 1982).

Following the success of the ALS, a Road Pricing Scheme (RPS) was in-

troduced in 1995. The way the RPS worked was similar to the ALS; under the RPS, the vehicles passing through the East Coast Parkway during the morning peak hours between 7.30 am and 8.30 am on weekdays, excepting the exempted vehicles, had to purchase a RPS license – priced at S$0.5 for motorcyclists and S$1 for other vehicles. As with the ALS, the RPS was also deemed effective in reducing congestion and increasing travel speed along the expressway.

However, these measures were not without problems. In fact, there is an important challenge inherent in demand management measures like the ALS and RPS. People often respond to a new policy and adjust their behaviour, which may undermine the effectiveness of the policy or create an unanticipated problem. For example, the government initially encouraged people to carpool through the exemption of HOVs and subsequently even set up special pick-up points outside the RZ for carpooling. However, this turned out to be a loophole of the ALS and eventually the HOV exemption was abolished in 1989 (Menon and Kuang, 2006). Another example is the adjustment of travel time and route by drivers to avoid the payment. The adjustment is desirable on its own from the perspective of reducing congestion that the ALS is targeted to reduce. However, it led to a transfer of congestion to a new time and location. For these reasons and to cope with changing traffic conditions, the ALS had to be adjusted several times by varying the entry fee and the period of chargeable peak hours (Lim, 2014).

Inadequate understanding of the behavioral response can also lead to inefficient use of resources. When the ALS was first implemented, its impact was too large and, as a result, roads were underutilised. The traffic volume during the restricted hours fell by 43 percent, even though the target was to reduce it by 25 to 30 percent (Phang and Toh, 2004). Another example is the Park & Ride scheme launched in 1975 to support the ALS. Under this scheme, motorists could park their vehicles in one of 15 fringe car parks outside the RZ and continue their journey using shuttle buses (Muthu, 1975). However, this scheme completely

failed as car parks were empty and the shuttle buses were underutilised. Motorists who decided to switch to buses did so from home and not from the fringe car park (Menon and Kuang, 2006).

Furthermore, the implementation of the ALS and RPS was inefficient and prone to errors, because they required dedicated license sale booths and visual monitoring for manual implementation. To address this issue, the government explored Electronic Road Pricing (ERP) and replaced the manual versions of the ALS and RPS with the ERP in April 1998 (Chin, 2005). In the ERP system, when a car passes under an on-site ERP gantry, the gantry communicates with the car's in-vehicle unit (IU) and deducts the ERP charge –which depends on the vehicle type, location of the gantry, time of the day, and day of the week – from the stored-value smartcard called CashCard inserted in the IU. The ERP gantries are also equipped with an enforcement camera system, which takes a picture of the offending cars, such as cars with no IU, no CashCard inserted in the IU, or insufficient balance in the CashCard.

Once an IU is installed, the ERP system is easy to use; drivers only need to insert a CashCard into the IU. Therefore, the installation of IUs was critical for successful implementation of the ERP system. The government started publicity campaign more than a year prior to the launch of the ERP system and from September 1997, the government started the IU-fitting program, which gave away IUs at no cost to vehicle owners if the IU is fitted during a particular period (installation costs S$150 otherwise). This program was implemented over a period of 10 months, so that there was no last-minute rush to fit the IUs. While the fitting of IUs was voluntary, more than 98 percent of registered vehicles were fitted with IUs at the end of the IU-fitting program.

The ERP system has been increasingly used across the city-state to control congestion, and there are 77 ERP gantries as of 2015 (Diao, 2019). The ERP system not only removed the need for manual enforcement but also allowed policymakers to implement the charges more flexibly, which in turn mitigated the

undesirable side effects of ALS and RPS. For example, by adopting shoulder-charging, in which the charges change gradually around the peak hours, the incentive for the drivers to wait just outside the chargeable areas was substantially diminished.

More importantly, in the initial years after its introduction, the ERP system successfully reduced traffic in the expressways by 15 percent and increased the average speed of motorists from 35 kilometres per hour to 55 kilometres per hour during the hours of operation of the ERP (Menon and Guttikunda, 2010). However, in spite of several benefits of the ERP, some people had concerns about the pay-as-you-use system. Drivers needed to pay a flat fee for multiple entry under the ALS, but under the ERP system, they have to pay a charge every time they pass a gantry during its operating hours. In addition to the regular ERP charge, there is also a penalty of S$10, if they pass through an operational gantry without a properly inserted CashCard or sufficient value in the CashCard (Land Transport Authority, 2019a). There has also been some unease about the lack of privacy that this system entails, because the commuter's travel and location patterns are recorded.

However, the diffusion of the IUs and CashCard also provides additional convenience to drivers as they can make payments without getting off the car. For example, many car parks in Singapore today adopt the Electronic Parking System (EPS), which operates like the ERP system. In EPS car parks, the parking charges are automatically calculated and deducted from the CashCard upon exit. For example, of the 2,108 car parking lots available in the HDBs, around 88 percent of them use the EPS (Housing Development Board, 2019).

While the ERP system provides greater flexibility and efficiency than the ALS and RPS, it requires heavy physical infrastructure such as overhead gantries and signage. Furthermore, the ERP charges that a driver incurs depend only on whether and when the car passes through the ERP gantries and not on how long the car stays on congested roads. To address these issues, the Land Transport

Authority (LTA) of Singapore is currently testing the next generation of the ERP system. The new system dispenses with the physical gantries by using satellites and charges motorists for the distance they travel on congested road (Tan, Christopher, 2016).

The measures discussed above were primarily intended to reduce the usage of cars. Singapore also implemented various policies to restrain the ownership of cars as well. Until 1990s, car ownership was restricted primarily by price policies, which included an import tax, a lump sum registration fee, an additional registration fee (ARF), and an annual road tax, based on vehicle capacity. These taxes and fees were increased substantially over time with an increasing car population. Between 1968 and 1990, the import tax rate increased from 30 percent to 45 percent, the registration fee from S$15 to S$1,000, and the ARF from 15 percent to 175 percent of the market value of the vehicle. The annual road tax has also increased from 10 cents to 70 cents or more per cc, depending on the engine of the car (Chia and Phang, 2001).

The government was, however, also concerned that a high ARF would discourage existing car owners from replacing their cars, or potential new car owners from buying new vehicles. Thus, when the ARF was increased from 55 percent to 100 percent in 1975, the government introduced the preferential additional registration fee (PARF), which provided a discount on the ARF when the car owner scraps a car within 10 years of age upon registering a new car. The amount of PARF was determined by the open market value of the car and engine capacity, but the scrap car prices were determined only by the engine capacity. As a result, the scrap car price was higher than the original purchase price of an inferior car in the same category, and many car owners enjoyed low or even negative cost of ownership (Chia and Phang, 2001). Furthermore, despite the rapid increase in the cost of owning cars, car ownership increased quite rapidly as the income levels went up. Between 1975 and 1989, the car fleet in Singapore grew by 80 percent from 142,000 to 257,000, even though the population

growth during this period was only about 30 percent (Fwa, 2016).

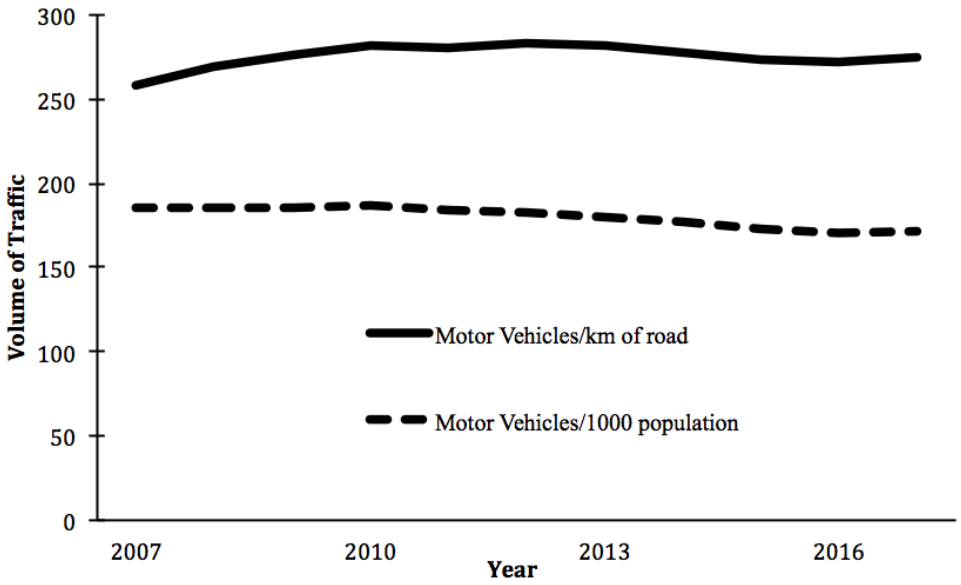
Against this backdrop, the government decided to depart from price policies and adopted a Vehicle Quota System (VQS) in 1990. Under the VQS, a buyer of a new car must purchase a Certificate of Entitlement (COE). COEs may be obtained in a public tender separated into different categories by the engine capacity and purpose of the car, and successful individual bidders pay the lowest successful bid price in a given category.

The VQS has clearly succeeded in containing the growth of car population in Singapore as the number of COEs to be issued can be chosen by the government. As of 2017, Singapore's total automobile population stands at 962,000, which translates into a linear density of 274 motor vehicles per kilometer. While this is among the highest in the world, this figure has changed little over the last decade. Further, the number of motor vehicles per thousand people actually declined slightly during the same period (Figure 4.2).

One consequence of using a quantity-based regulation like the VQS is that the prices may become volatile. Indeed, the COE prices have fluctuated substantially depending on the supply of COEs and economic environment at the time of bidding. For example, the COE price for Category A (small cars up to 1,600cc and 97kW) had gone up from an all-time low of S$2 on November 19, 2008 to a historical high of S$92,100 on January 9, 2013. The price difference between the two periods denotes several times the pre-tax price of many small cars. Such a large fluctuation can, therefore, potentially penalise people who happen to be in dire need of cars at the time of high COE prices, which, for example, may include families with small children, elderly people, and disabled members.

Because of the various taxes and fees, owning a car in Singapore has been very expensive. For example, a Honda Civic was reported to cost S$149,000 in 1997, of which the government would collect around S$100,000 in taxes and fees (Phang and Toh, 1997). Thus, to allow more people to own a car without

Figure 4.2: Trend in the Volume of Traffic, 2007-2017



Source: 2017 Annual Vehicle Statistics

increasing the fear of congestion, the Weekend Car (WEC) scheme was implemented in 1991. Under the WEC scheme, the car owners were required to obtain a COE for the new category created for weekend cars under the VQS. While they were restricted to drive only during the off-peak hours (7pm to 7am on weekdays, after 3pm on Saturdays, and all day on Sundays and public holidays), they could enjoy reduced annual road tax and tax rebates on the registration fee, import duty, and COE premium, up to S$15,000. If the owners of the weekend cars wanted to use their cars on weekdays, they were required to purchase a S$20 coupon for each day.

This policy, however, suffered from a loophole, as one could purchase a weekend car and use it like a normal car (Leong, 1994). In particular, the WEC scheme favored big (and expensive) cars and owners of such cars could use up the savings from the purchase of weekend cars to buy a sizeable number of daily coupons. In July 1994, the discount on the COE premiums for weekend cars relative to normal cars was so large that the up-front combined savings from this discount and tax rebates combined were more than sufficient to finance 10

years of S$20 daily coupons (Phang et al., 1996). To address this loophole, the WEC scheme was replaced by the Off-Peak Car (OPC) scheme, in which car owners received an upfront rebate of S$17,000 and discount on annual road tax. The OPC was further revised in 2010 to the Revised Off-Peak Car scheme to encourage drivers to join the scheme. Nevertheless, both the number and proportion of off-peak vehicles (cars and station wagons) registered reduced from 50,040 (8 percent of 595,185 vehicles) in 2010 to 30,469 (5 percent of 602,311 vehicles) (Tang, 2016).

Singapore's two types of measures, one to reduce the usage and the other to reduce the ownership of cars, were overall successful as Singapore managed to maintain healthy traffic flow and contain the growth of vehicle population, particularly in comparison to the experiences of other cities. However, some policies did not work in the way they were expected and adjustments were needed. Singapore's experience demonstrates the difficulty of fully anticipating behavioural responses and the importance of calibrating the policies swiftly as needed.

Investing in Public Transportation System for Liveability and Sustainability

While the policies to manage traffic congestion have been successful, they may potentially come at a high welfare cost if they simply result in reduced mobility of people. Hence, it is important to improve the pull factor by making the public transportation system accessible and attractive to all residents.

At the time of Singapore's independence in 1965, buses were practically the only mode of public transportation. However, the bus transportation system was inadequate and inefficient. There were 11 bus companies, which included the government-owned Singapore Traction Company (STC) and 10 Chinese companies, and there was no planning or coordination among them to build a bus

system to serve the public. The lack of integration often resulted in long and inconvenient journeys with multiple transfers (Lew and Choi, 2016) and the low demand areas were not covered (Looi and Choi, 2016). Badly maintained buses broke down regularly all over town and there were more buses in for repairs than there were on the roads (Sharp, 2005). Buses also did not run on time, partly because workers often went on strikes and demanded a higher pay and better working condition. The bus fleet in Singapore was small relative to the demand and these issues exacerbated the overcrowding of buses.

Furthermore, corrupt practices were also prevalent. For example, many conductors pocketed passengers' fares or resold the paper tickets if they could and their bosses were no better. It was generally accepted that the bus company owners were little more than gangsters, or else in the grip of gangster protectors. As such, a sizeable number of bus companies was making losses. For example, the total accumulated losses for STC was S$5.7 million between 1964 and 1969 (Sharp, 2005).

The problems with the bus transportation system were well recognised even before 1960s. Following the Great STC Strike in 1955 that lasted 142 days, the Report of the Commission of Inquiry into the Public Passenger Transport System of Singapore – also known as the Hawkins Report – called for the consolidation of 11 companies and a single licensing authority. The latter was realised as formation of the Omnibus Services Licensing Authority (OSLA), but it lacked power to effectively regulate the STC. For example, the OSLA could not withdraw any of the STC's routes, even if the STC was inefficiently managed (Looi and Choi, 2016).

It was not until the early 1970s that a drastic reorganisation of the bus services finally took place. The first turning point was the publication of the White Paper on the Reorganisation of the Motor Transport Service of Singapore in 1970 (Singapore Registry of Vehicles, 1970), which described the bus services at that time as follows:

No survey needs to be conducted to establish the fact that there is an inadequate number of buses in service for the public. The large crowds waiting patiently over long spells at bus stops and the existence of thousands of 'Pirate Taxis' for more than 15 years, are plainly visible.[29]

The White Paper called for, among others, the empowerment of OSLA, eradication of pirate taxis, creation of more job opportunities with increased bus fleet, reorganisation of the STC, and amalgamation of bus companies to improve public bus services. The White Paper lead to the commissioning of A Study of the Public Bus Transport System of Singapore, also known as Wilson report, which provides specific recommendations and implementation plans (Wilson, 1970). What the White Paper and Wilson report called for were implemented through early 1970s, even though the road to rationalisation of the bus system was full of ups and downs (Looi and Choi, 2016).

While we are not aware of any rigorous evaluation of the impact of reorganisation of bus services on the environment, the pollution problem was well recognised in the White Paper and it is likely that replacement of old buses and improved maintenance have contributed to the reduction of pollution from buses. Old private buses and privately-owned taxis were running all over the place, full of black smoke as Mr Tan Gee Paw, a former Permanent Secretary of the Ministry of Environment, recalls (Centre for Liveable Cities, 2016).

Because the buses have limited capacity to transport people and are subject to delay due to traffic congestion, the possibility of building a Mass Rapid Transit (MRT) rail transport system, which can potentially transport hundreds of people at once without being affected by traffic congestion, was debated throughout 1970s. After much deliberation and taking into account potential costs and benefits of the MRT system, the government gave the green light to the construction

[29]Pirate taxis are the private cars operating as taxis without licenses. There were some 6,000 pirate taxis, even though only 3,800 taxi licenses were issued by 1970. While these pirate taxies had poor service standards and irregular fare structures and were a cause of road safety issues, their services complemented inadequate bus transport services then (Looi and Choi, 2016).

of MRT in 1982 and the first two lines opened five years later in 1987.

Since early 1990s, efforts have been made to integrate the bus and MRT networks. The bus routes have been revised to complement, rather than compete against, the MRT lines. Fare collection system was also integrated across different public transport operators using store-valued magnetic strip tickets, which enabled cashless payment. These tickets were later replaced by contactless smartcards called EZ-Link cards. The integrated payment system enabled distance-based charging – in which fares are calculated by the travel distance regardless of the number of transfers – and the EZ-Link cards are accepted as a mode of payment in many shops across Singapore. Most new MRT stations are underground such that commuters do not need to be exposed to hot and humid weather in Singapore. As of 2018, there are five MRT lines and three Light Rail Transit lines and an additional three lines are being planned or constructed. With the completion of these three lines and planned extensions of existing lines, the government expects that 8 out of 10 households will be within a 10-minute walk from a train station by 2030 (Chew, 2016). Through the expansion of network, the MRT system has increasingly become an integral part of the public transport system in Singapore.

As Singapore built up a better functioning and more sophisticated public transportation system, the focus of Singapore's transport policy has also shifted from just building physical infrastructure towards better user experience of public transport. To achieve better service standards and operational efficiency, measures have been taken to increase competition and contestability. For example, additional bus and MRT companies were allowed to enter these previously monopolised markets.

From 2016, the government has progressively implemented the Bus Contracting Model (BCM), where the LTA owns the bus infrastructure – including buses, depots, and bus management systems – and specifies the requirement for the bus services to be bid competitively. Under the BCM, the contracted bus op-

erators are paid the fees to operate the services, while fare revenues are retained by the government (Land Transport Authority, 2014). Since 2016, the operation of the MRT lines has also shifted in steps towards a somewhat similar model under the New Rail Financing Framework – in which the operating assets are held by the LTA and operators pay for the license to operate. Both the MRT and bus services appear to have made notable improvements in the quality of service in recent years. For example, the reliability of the MRT network as measured by the Mean Kilometre Between Failure has dramatically improved from 93,000 train-km in 2014 to 680,000 train-km in 2018 (Tan, Christopher, 2019).

With various measures and policies implemented by the government and public transportation operators, the public transportation system in Singapore has become more attractive to the general public. For example, the share of residents aged 15 and older, who take either the MRT, bus, or combination of both, to work has gone up from 50.7 percent to 58.7 percent in a decade's time according to the General Household Survey conducted in 2015 (Lee, 2016). Indeed, boasting of one of the best public transportation systems in the world, Singapore ranks first in the overarching urban mobility ranking of 24 global cities (Knupfer et al., 2018) and eighth out of 100 cities around the world in the Sustainable Cities Mobility Index 2017 (Arcadis, 2017).

In sum, Singapore has enjoyed remarkable success in raising the standards of public transportation system from a chaotic state in 1960s to a world-class standard today. The affordable, reliable, and efficient transportation system in Singapore positively contributes to its liveability today.

Transport Policies and Technologies to Move Forward

As we have seen in the previous two sections, Singapore has implemented a number of measures to discourage the ownership and usage of cars and to encourage the use of public transportation by making it more attractive. Singapore

has also taken measures to improve the environment for pedestrians and cyclists by, for example, building sheltered walkways, pedestrian overhead bridges, and designated bike paths. The rules about bicycles and personal mobility device – where users are allowed to use them and how fast they can move with them – have also been introduced for the safety of pedestrians and sustainable coexistence of different modes of transport. These measures and policies would help promote active mobility and achieve a “car-lite" society.

Singapore has also implemented measures to make the city more sustainable. For example, Singapore has implemented progressively more stringent emission and noise standards for vehicles and quality standards for automotive fuels. Financial incentives have also been introduced to encourage people to buy cleaner cars or to replace older and more polluting vehicles with cleaner ones. Despite these efforts, it remains imperative for Singapore to further improve environmental performance indicators to build a sustainable city, particularly given that the total population is projected to increase to 6.2 million by 2030 from 5.6 million as of 2018 (World Bank’s population estimates and projections), which would further increase the strain on the environment.

In particular, transport sector can play an important role in reducing air pollution in Singapore. This is important, because air quality in Singapore needs substantial improvement to achieve the Air Quality Guidelines (AQG) by the World Health Organization (WHO), which provides a guidance in reducing the health impacts of air pollution. In 2017, nitrogen dioxide (NO_2) and carbon monoxide (CO) were the only pollutants that were within the WHO AQG. Sulphur dioxide (SO_2), fine particulate matters with a diameter of 2.5 μm or less ($PM_{2.5}$), and coarse particulate matters with a diameter of 10 μm or less (PM10) were within the WHO Interim Targets, which are less stringent than the WHO AQG and used in high pollution areas to progress towards the WHO AQG level. The level of ozone (O_3) even exceeded the WHO Interim Target. In Singapore’s own Pollutant Standards Index which uses the measurements of six pollutants

mentioned above (i.e., NO_2, CO, SO_2, $PM_{2.5}$, PM_{10}, and O_3), only less than 10 percent of the days had 'good' air quality and almost all the remaining days had 'moderate' air quality both in 2016 and 2017 (Environmental Protection Division, 2017). Because vehicles contribute directly or indirectly to the ambient concentration of these pollutants,[30] it is imperative that the emissions from the transportation sector be reduced to improve the air quality of Singapore.[31]

The LTA has adopted various measures over time to help reduce air pollution through less carbon emission from cars, and at the same time raise consumer awareness about the fuel efficiency of new cars and its potential impact on the environment. Under the Carbon Emissions-Based Vehicle Scheme, car owners, who had registered their cars from 2013 onwards, were required to pay a surcharge or enjoyed a rebate on the car registration fee, depending upon the emission levels of carbon dioxide. This scheme was replaced by the Revised Carbon Emission-Based Scheme in 2015 and the level of carbon emission to enjoy the rebate was lowered. The scheme was further revised in 2018 and the emission levels of four other pollutants including hydrocarbons, carbon monoxide, nitrogen oxide, and particulate matter were also taken into account under the Vehicular Emissions Scheme. In addition, under the Fuel Economy Labelling Scheme introduced in 2012, a vehicular emissions label must be displayed in the showroom to make it easy for consumers of cars or light goods vehicles to compare the vehicle's fuel economy and emissions of major pollutants. Thus, economic incentives have been at the core of Singapore's policy to reduce air pollution from the transportation sector.

[30]This does not mean that vehicles are an important source of emissions for all these pollutants. For example, vehicles only account for 0.1 percent of SO_2 emissions, whereas refineries account for over 90 percent in 2017 (Environmental Protection Division, 2017).

[31]Transboundary pollution can also be an important source of air pollution in Singapore. In particular, forest fires in Indonesia and Malaysia have created haze, which became a major public concern from time to time, particularly in 1997 and 2013 (See, for example, Quah (2002) and Forsyth (2014)). Singapore has taken some steps domestically such as the enactment of Transboundary Haze Pollution Act (Lee et al., 2016) to address this issue. However, detailed discussion of transboundary pollution is out of the scope of this paper. We shall briefly discuss the impact of climate change at the end of this paper.

Besides air pollution, noise pollution in Singapore also needs to be addressed for a better living condition of the city. A study by researchers from the National University of Singapore found that the outdoor sound level throughout the day in Singapore is about 69.4 decibels (Ng and Xi, 2017), which is still within the WHO's threshold noise limit of 70 decibels but exceeds the recommendation of 67 decibels by the National Environment Agency (NEA). The main contributors to noise pollution in the city are the MRT and the vehicular traffic in the expressway. Noise barriers, which are able to reduce noise from passing trains by at least 5 decibels, have been built along the MRT tracks since 2013 to alleviate the situation.

Going forward, technology will play a critical role in making Singapore's transport system cleaner and more convenient, and various initiatives are already in place. One notable example is the development and testing of Autonomous Vehicle (AV) technology. With the endorsement of the LTA since 2015, Singapore is currently ranked second (only behind the Netherlands) in terms of the readiness for AVs (The Straits Times, 2019). Autonomous scheduled buses and on-demand shuttles are set to go on board in Punggol, Tengah, and Jurong Innovation Districts from the early 2020s. Electric car sharing is on the rise recently, and the number of electric cars is expected to grow to 1,000 with access to 500 charging stations across the island by 2020 (Abdullah, 2018).

The public transportation system can also improve with the use of new technology. Automated vehicle inspection system and automatic track inspection system have been used to inspect, respectively, trains cars and tracks in some MRT lines in recent years. The use of drone technology is also being explored as an option to capture images and videos of problems within the tunnel (Kor, 2018). These technologies will enable more efficient maintenance of the MRT system.

Technology can also make the public transportation system more convenient and accessible to all. For example, new crowd monitoring systems are in place

to inform the commuters of relatively emptier cabins. Another example is the use of the Common Fleet Management System, through which commuters can learn about the expected arrival time of a bus and bus drivers can monitor deviation from the scheduled headway (Sim, 2014). At four MRT stations, new hands-free payment, which uses bluetooth-enabled mobile device or a radio-frequency identification test card, is being tested with the involvement of people with disabilities (Paramanantham, 2018). These technologies will contribute to the improvement of the efficiency, accessibility, and inclusiveness of the MRT system.

The government of Singapore is also investing heavily in research and development of the transport sector and has taken a host of initiatives. The LTA has allotted S$25 million for mobility-related research and technology trials over the next five years that would shape the future of transport in Singapore (Tan, Christopher, 2018). Together with Singapore University of Technology and Design, LTA set up a transport research centre that will foster collaborative research in key areas such as cybersecurity, automation and robotics, and data analytics, behavioral studies and user-centric design in transport solutions (Channel News Asia, 2017a).

As described in the Land Transport Master Plan 2040, Singapore envisions a transport network that is convenient, well-connected, fast, and more inclusive and creates a safer, healthier and more liveable environment (Land Transport Authority, 2019b). Singapore aims to achieve 20-Minute Towns and a 45-Minute City – where one can reach the nearest neighbourhood centre within 20 minutes and one's workplace within 45 minutes during peak periods by combining different modes of transport such as walk, cycle, bus, and MRT. Singapore also aims to make transport more accessible and inclusive by creating, for example, more wheelchair-accessible facilities, priority queues and cabins, resting points, and accessible overhead bridges. Singapore also envisions a land transport system that creates a safer, healthier, and more liveable environment by

adopting, for example, more stringent emission and noise standards for vehicles and quality standards for automotive fuels.

4.4 Tackling the Challenge of Increasing Waste in Singapore

As Singapore becomes more affluent, its residents consume more goods and services. Not surprisingly, the massive rise in the standards of living has been accompanied by a rapid increase in the production of wastes. Between 1970 and 2017, the amount of solid waste disposed of in Singapore increased from 1,260 tons a day to 8,443 tons a day, at an average rate of 4.1 percent per annum (Environmental Protection Division, 2017). This is lower than but comparable to the annual growth rate of 4.7 percent in real GDP per capita, computed from the World Development Indicators.

A Brief History of Waste Management in Singapore

In the early stages of development, wastes were separated to recover the recyclable and reusable products in Singapore. This was done due to economic viability rather than environmental reasons (Bai and Sutanto, 2002). The remaining wastes were mostly landfilled. However, Singapore has limited area for landfill and the need to contain the volume of wastes for landfill had become increasingly apparent by the late 1970s. Following the opening of the first incinerator in 1979, Singapore steadily increased the incineration capacity, because incineration can reduce the volume of wastes by up to 90 percent.[32]

Today, wastes that are not recycled are mostly incinerated by the four incineration plants that are in operation. The heat produced from incineration is used to generate electricity. Some of the generated electricity is used for the operation of the incineration plant, and the excess is exported to the national grid. These four plants generate about two percent of Singapore's total elec-

[32]The Ulu Pandan Incineration Plant. This plant operated until 2009.

tricity demand (Singapore Energy Market Authority, 2018a). Besides energy, ferrous and non-ferrous metals are also recovered in a metal recovery facility from incineration bottom ash generated by the incineration plants. The remaining ashes are then moved to the Tuas Marine Transfer Stations and shipped to Semakau Landfill, which is located off the main island. The Semakau Landfill is currently Singapore's only landfill facility covering an area of 350 hectares.

The Semakau Landfill had an initial landfill capacity of 11.4 million m^3 when it commenced in 1999, and its capacity has increased by 16.7 million m^3 when its Phase II development was completed in 2015. It is expected to meet Singapore's solid waste disposal needs up to 2035 (Sidik, 2015). However, increasing incineration and landfill capacities do not fundamentally address the issue of ever-increasing production of wastes. Therefore, the Singapore government has increased the efforts to systematically manage wastes, particularly since the 1990s. For example, the Waste Minimisation Unit was set up in 1991 by the Ministry of Environment and upgraded to form the Waste Minimisation Department (WMD) in 1992 with the functions to develop, plan, promote, and implement waste minimisation and recycling programs and schemes in Singapore (Seik, 1997).

The Singapore Green Labelling Scheme (SGLS) was also launched in 1992 to endorse industrial and consumer products that have less undesirable effects on the environment, and is administered by the Singapore Environment Council. Products that use recycled materials or produce less waste are eligible to apply for the label. The green labels like SGLS enable potential buyers of greener products to readily identify them and possibly nudge them to purchase. The SGLS has expanded substantially in product coverage with over 3,000 certified unique products and is the region's most established eco-labelling scheme today (Singapore Green Labelling Scheme, 2019).

Catching up with Neighbors in Waste Management

Despite various policies implemented to date, Singapore has not been particularly successful in containing the amount of wastes produced. For example, the amount of municipal solid wastes generated in Singapore was around 700 kilogram per capita in 2000, up from around 550 kilogram per capita in 1985. This figure is substantially higher than the corresponding figure of 400 kilogram per capita or lower in 2000 in Japan, Korea, and Taiwan (Lu et al., 2006). These countries have stabilised or lowered their waste generation since 1985.

More recently, Singapore has also increased efforts to promote the 3Rs – Reduce, Reuse, and Recycle. Singapore has steadily made progress in increasing the rate of recycling with the share of wastes recycled standing at 61 percent in 2016, up from 47 percent in 2003 (National Environment Agency, 2016). The most notable increase in the rate of recycling was witnessed in paper/cardboard, horticultural wastes, wood, and scrapped tyres.

However, there has been a wide variation in the rate of recycling across different kinds of wastes. For example, the recycling rates for construction debris, ferrous and non-ferrous metals, and used slag have always been very high (90 percent or above) at least since 2003, such that the increase in the rate of recycling was at best modest in recent years. These types of wastes are mostly industrial and tend to be generated in large quantities from a relatively small number of locations or firms. This, in turn, makes recycling comparatively easy because the economic benefits obtained from recycling relative to the costs of material collection and recovery tend to be high. Further, it is relatively easy to regulate a small number of firms that generate certain specific types of wastes.

On the other hand, for some other items such as food, ash/sludge, textile/leather, plastics, and glasses, the recycling rates remained low (20 percent or below) between 2003 and 2016. With the notable exception of ash/sludge, a sizable fraction of these wastes comes from a large number of small waste pro-

ducers such as households and small businesses (as opposed to large factories and plants). This tends to drive up the costs of material collection and recovery relative to the value of these wastes when recycled. Further, the costs of monitoring and enforcement tend to be high when there are many producers of wastes. Of course, the costs discussed above are not the only important factors that would significantly affect the recycling rate. For example, the technology for storage and processing of collected materials as well as the economic benefits of reclaimed materials also play an important role (Butlin, 1977). In fact, households today still sell paper wastes and some other unwanted items of value to rag-and-bone men, locally known as karung guni men. Nevertheless, the difficulty associated with collecting and recovering materials from a large number of small sources like households is likely to remain as an important challenge for recycling.

This, of course, does not imply that recycling of household wastes is impossible or makes no economic sense from the societal perspective, even in the presence of relatively large costs of material collection and recovery. This is because the total private cost, or the sum of costs paid collectively by households, of disposing household wastes is not the same as the corresponding social cost. Consider the cost of refuse collection for households as an example. The private cost, or the cost that households pay for refuse collection, is determined by the type and location of residence and not by the volume of household wastes in Singapore. Therefore, even if households marginally increase the amount of wastes, the private marginal cost, or the cost that the household bears for disposing the incremental amount of waste, is zero. On the other hand, the social marginal cost, or the cost of disposing the incremental amount of waste for the society, is clearly positive. Similarly, the social net benefit of recycling may be positive even when the private net benefit for recycling is negative.

Furthermore, recycling wastes may be inconvenient in comparison to simply throwing them away. This may be true everywhere, because it is easier to

dump everything together than to separate different types of wastes. Nevertheless, Singapore's housing situation arguably makes it too easy to throw away wastes instead of recycling. That is, in a typical housing unit in private apartments and publicly provided HDB flats, there is a single rubbish chute from which households can throw away most of their wastes. At the bottom of the chute, there is normally a large waste collection container, which is transferred to the garbage collection truck. The rubbish chute provides the convenience of being able to dispose wastes anytime without going out of the unit. In contrast, recycling typically requires households to bring their wastes to a designated bin outside their units. Moreover, the chute also enables households to dispose their wastes without being observed by others. Therefore, it provides anonymity and creates no peer pressure for source separation for recycling. This means that the private marginal net benefit of recycling may be substantially lower than the corresponding social marginal net benefit.

This gap between private and social marginal costs would explain why the recycling rate for household wastes remains low at only 21 percent in 2016 in contrast to the corresponding rate of 76 percent for industrial wastes. It is also notable that the household recycling rates in other Asian territories such as Taiwan and South Korea are around 40-50 percent (Wee, 2017), even though international comparisons require a caution because of various methodological difficulties associated with the measurement of recycling rates.

Exploring Better Waste Management Practices

The government is well aware of the issue of waste management and a number of measures have been put in place over the last few years. In 2014, the government announced that all new public housing projects will be fitted with recycling chutes and every HDB block be provided with a recycling bin. From 2018, new non-landed private developments are required to have dual chutes and

existing private condominiums one recycling bin per block (Boh, 2017; Tan, Audrey, 2018a). Another example of modern and efficient waste management is automated waste collection through the Pneumatic Waste Conveyance System, which has already been introduced in new HDB housing areas, such as Tampines North, Punggol North, and Bidadari. In this system, wastes are sent to a central location through an underground network of concealed pipes. Further, new technologies are being tested and implemented to enable cleaner and more efficient refuse collection. For example, in Punggol's Northshore District, a Smart Pneumatic Waste Conveyance System is installed to monitor the waste disposal pattern and reduce the resources needed for refuse collection (Yeo, 2015). These measures have been taken to improve the infrastructure for recycling, facilitate the participation of households in recycling, and increase the domestic recycling rate.

Besides recycling infrastructure, the government also plans to expand the overall waste management infrastructure. A new plant, TuasOne Waste-to-Energy Plant, has been under construction using the Public Private Partnership scheme, making use of the design-build-own-operate model. The plant was designed to have a contracted incineration capacity of 3,600 tons per day exclusively to the National Environmental Agency for a period of 25 years from 2019 to 2044 and a generation capacity of 120 MW (Hyflux, 2015). The plant can use the electricity for its operation and export the excess electricity to the grid.[33]

The NEA is also planning the development of an Integrated Waste Management Facility (IWMF) to meet Singapore's long-term waste management needs. The IWMF will be co-located with the Tuas Water Reclamation Plant (TWRP) to maximise their synergies and to optimise land use footprint. The IWMF will be equipped with several state-of-the-art solid waste treatment technologies that

[33]There is some uncertainty about the fate of the TuasOne project at the time of writing, because Hyflux, which implements the projects together with the Mitsubishi Heavy Industries through a project company, became insolvent and has been in the midst of debt restructuring (Leong, 2018). Even if debt restructuring is successful, the completion of the project has already been delayed to early 2020 due to lack of funding (Leong, 2019).

will enable it to effectively handle multiple waste streams including incinerable wastes, recyclables, source segregated food waste, and dewatered sewage sludge from the TWRP, and optimise resource and energy recovery while minimizing environmental impact. The IWMF is expected to complete in 2027 and will have a capacity to incinerate 5,800 tons of waste per day (Boh, 2016). The improved waste management infrastructure through these and other efforts will help Singapore cope with increasing wastes.

In the long run, however, further promotion of the 3Rs will be needed for Singapore to move towards a zero waste nation, which is one of the focus areas of the Sustainable Singapore Blueprint (Ministry of the Environment and Water Resources, 2017). For example, work places have been required to report waste data and submit waste reduction plan from 2014 (Environmental Protection Division, 2017). Since 2016, the Singapore Exchange (SGX) introduced sustainability reporting for all publicly listed companies on a "comply or explain" basis (Tan, Nicole, 2016). In a national push to effectively manage waste, companies will have to report the packaging materials used in their products and their package waste reduction plans by the end of 2020 to the NEA (Wong, 2018). These measures will make firms conscious of the environmental impact that they create.

In contrast to the policies for industrial wastes, few measures have been taken to promote source reduction and recycling of household wastes. For most recyclable household wastes, there is currently no price-based system such as deposit-refund system or recycling subsidies, except that public waste collectors have implemented cash-for-trash programs under which households can exchange some recyclable items for cash in some HDB neighbourhoods.[34] There are also no economic incentives for households to reduce other household wastes either, because the refuse collection fee depends on the type of the household's residential unit but not on the amount of waste that the household generates, as

[34]See Palmer et al. (1997) for the property of these policies.

noted earlier.

This is in stark contrast to Japan, Korea, Taiwan, and some other countries in Europe and elsewhere. These countries have a strict source separation policy and a unit pricing system (UPS) in which households' payment for waste collection and disposal services varies according to the volume or weight of the waste collected. In a typical implementation of a UPS, households have to i) pay a fixed fee for the collection of a fixed amount of waste in a fixed time interval (and pay an extra amount in excess of that amount), or ii) purchase designated trash bags or stickers for their wastes to be collected. Under the UPS, households have an incentive to reduce wastes and increase recycling, provided that the policy is effectively implemented. However, it would require the adoption of some technologies to effectively implement a similar policy (Hong, 1999) in places with a single rubbish chute to be able to identify and punish the violators of the rules of a UPS. Such technologies may include a combination of Radio-Frequency Identification (RFID), censors or cameras, and tag. Even if the technical problem of monitoring is resolved, implementing a pay-as-you-throw policy may be politically difficult as it is likely to be unpopular. For example, in a recent survey of 100 readers of The Straits Times, 69 opposed this idea (Teh, 2019).

In Japan, Korea, Taiwan, and various other high-income countries, the burden of recycling has shifted from municipalities or households to the producers and importers through an Extended Producer Responsibility approach for some domestic electric and electronic items such as refrigerators, washing machines, personal computers, and televisions. Singapore will also follow this model and the Ministry of Environment and Water Resources will implement a mandatory e-waste management system by 2021 (Channel News Asia, 2018). Incentives or taxes will also be used to prod manufacturers and importers to meet specific recycling targets (Boh, 2018).

The incentive policies discussed above may work if they are appropriately

implemented. Nevertheless, economic incentives alone would be insufficient for two reasons. First, in a study of 10 OECD countries, non-economic motivations are very important in explaining household recycling behavior (Halvorsen, 2012). A strong moral commitment, a high expectation about the effectiveness of recycling to improve environmental quality, and a positive attitude towards environmental policies in general are found to be among the most important factors influencing the recycling rate. Second, even if non-economic motivations were not very important, it would be impractical to manage everything through incentives. Consider food waste as an example. It is an important problem in the island state with 810 million kilogram of food wasted in 2017, half of which is from households. However, it will be difficult to regulate domestic food waste by economic incentives alone as it will be too costly to monitor. Therefore, it will be critical to advance the understanding of the 3Rs and foster broad environmental consciousness.

There are grassroots-level initiatives to this end. For example, the Clean Plate Campaign has been running a campaign in schools and more recently in hawker centres to raise awareness of the environmental and societal impact of food wastes (Liew, 2018). Zero Waste SG, an environmental group, provides a variety of information on the 3Rs and runs campaigns to encourage recycling and to reduce the consumption of single-use plastic disposables by bringing reusable alternatives (Zero Waste Singapore, 2018).

The government is also stepping up the efforts in this direction. The Ministry of Environment and Water Resources designated 2019 as the Year Towards Zero Waste (Ministry of the Environment and Water Resources, 2019). The aim is to raise the awareness of waste issues and build a strong 3R culture. Singapore has set itself a target of achieving a recycling rate of 70 percent by 2030. Both the domestic and industrial sector have to play a pivotal role in meeting this goal. The domestic [non-domestic] recycling rates are expected to go up from 22 [74] percent in 2018 to 30 [81] percent in 2030. Among other objectives, this

initiative will also aim to raise awareness about reducing e-waste and packaging waste, including the use of plastics. These efforts may change, if slowly, the environmental attitude and behaviour of the residents of Singapore and lead to a reduction in the waste generated and disposed.

4.5 Meeting Water Needs of the Resident

With its tropical climate, Singapore has abundant rainfall with the annual average of 2,340 millimetres, well above the global average of 990 millimetres. However, there is limited scope for capturing and storing the rainwater, because of the limited land space. Nevertheless, Singapore provides a great success story in both demand- and supply-side water management.

As a country highly dependent on import of water from Malaysia, which has become a political issue from time to time, since its independence in 1965, diversifying water sources has been imperative to Singapore. Meeting the water demand is likely to continue to pose an important challenge, as the population is projected to increase substantially over the next decade and as the problem of water scarcity in Singapore is projected to be among the severest in the world, because of the depletion of surface water in the coming decades (Luo et al., 2015). Nevertheless, Singapore has an ambitious goal of achieving self-sufficiency in water resource by 2061 through local catchment, water reclamation, and desalination of seawater.

We first review the supply-side policies, which use the four national taps of imported water, water from local catchment, reclaimed water, and desalinised water. These policies have been promoted by the Public Utilities Board (PUB)-Singapore's National Water Agency, which is responsible for the collection, production, distribution, and reclamation of water. We then evaluate the demand management policies through water pricing and water conservation programs.

Manging Water Supply through the Four National Taps

Water imported from Malaysia has been an important source of water for Singapore since its independence. The two water agreements, collectively known as the Johor Water Agreements, have allowed Singapore to import raw water at 3 sen (S$0.01 by the market exchange rate) per thousand gallons and Malaysia to buy treated water at 50 sen (S$0.17) per thousand gallons up to a certain limit. The first agreement signed in 1961, the Tebrau and Scudai Water Agreement, already expired in 2011, and the second agreement signed in 1962, the Johor River Water Agreement, will expire in 2061. The price of water under these agreements has been a source of contention between the two countries. For example, Malaysia's Prime Minister Mahathir Mohamad has reportedly criticised the 1962 agreement as 'too costly' and 'ridiculous' (Naidu, 2018).

To reduce reliance on imported water from Malaysia, there has been a concerted effort to achieve self-sufficiency in water supply by harnessing alternative sources. One important alternative 'national tap' is the rainwater in Singapore. Singapore is indeed one of the few countries where rainwater is systematically collected, treated, and used for the purpose of drinking. The rainwater collected through an extensive system of drains, rivers, and canals is passed on to one of the 17 reservoirs.[35] The water is then treated to make it potable. With the completion of the Marina, Punggol, and Serangoon reservoirs in 2011, Singapore's water catchment area now comprises of two-thirds of Singapore's land surface area (Public Utilities Board, 2018b). The system for rainwater collection is strictly separated from the sewage system to prevent the pollution of drinking water (Tan, Yong Soon, 2017).

Another important tap is the reclaimed water called NEWater. NEWater is produced in water reclamation plants, which collect and treat used water by microfiltration, reverse osmosis, and ultraviolet disinfection to make it potable.

[35]The system for collecting rainwater, particularly stormwater, is also important for flood management. See, for example, Public Utilities Board (2014).

NEWater has been available since 2003 and scientifically tested to be well within the WHO's safety requirements and is, in fact, cleaner than other water sources in Singapore. Nevertheless, there is some skepticism about NEWater among the public, and only 74 percent of the people approve of NEWater as suitable for drinking according to a survey (Timm and Deal, 2018). Currently, NEWater is widely used in industrial and commercial sectors, including wafer fabrication plants where the required water quality is more stringent than that for drinking water. NEWater produced in five existing water reclamation plants supplies 40 percent of Singapore's current water demand today. It is expected to meet 55 percent of the water needs by 2060.

Finally, as a country surrounded by the sea, Singapore has huge potential to transform sea water into potable water. Currently, desalinated water produced from three desalination plants meets 30 percent of Singapore's water demand (Public Utilities Board, 2019). Despite the population growth and projected increase in water demand, desalinated water is still expected to meet 30 percent of water demand in 2060. Thus, NEWater and desalinated water combined are expected to meet 85 percent of Singapore's water requirement by 2060.

The increased reliance on local catchment, reclaimed water, and desalinised water would reduce the dependence on imported water from Malaysia and help achieve sustainable water supply. Nevertheless, the reliance on reclaimed and desalinised water implies increased energy consumption per unit of water supplied, because both reclaimed and desalinised water currently use reverse osmosis for their production, which is energy-intensive. Therefore, it is important to find more energy-efficient ways to reclaim or desalinise water. Indeed, ongoing research explores alternatives such as electrodeionisation and biomimicry.

Managing Water Demand through Prices and Conservation Programs

To ensure a sustainable supply of water, adequate demand management policies must complement the supply-side policies so that no drop of water is wasted. Broadly speaking, the PUB has implemented the following three types of policies to manage demand: water pricing, mandatory water-efficiency labelling, and water conservation programs. Below, we review each type of policies.

Among these types of policies, pricing policy is arguably the most important policy instrument to signal the scarcity of the resource and to give the end users of water a right incentive to conserve water. The water price in Singapore takes into account the entire national water system's costs and consists of water tariff, water conservation tax, and waterborne fee. Water tariff reflects the cost of collection, treatment, and distribution of water, whereas water conservation tax is levied to create awareness among Singaporeans about the scarcity value of water and to encourage water conservation. Waterborne fee is collected to defray the cost of treatment of used water and maintain the used water network (Public Utilities Board, 2018c). Each of these three price components depends on the type of water (e.g., potable water, industrial water, and NEWater) and, for households, whether the cutoff level of 40 m^3 per month – above which higher rates apply – is exceeded. For households with monthly consumption below the 40 m^3 threshold, water tariff, water conservation tax, and waterborne fee are respectively S\$1.21/m^3, S\$0.61/m^3, and S\$0.92/m^3, as of March 2019.

Water prices in Singapore were increased for the first time since 2000 in two steps – in July 2017 and July 2018 – to accommodate the rising costs of producing high quality recycled and desalinated water. Even though the price increment was implemented over two years, there was an overall prince increase of 30 percent. Because water is a necessity and has no close substitute, a substantial increase in water price can have a severe negative impact on poor house-

holds. For this reason, price measures to conserve water are often controversial around the world. Singapore mitigated this issue by increasing the U-save rebates, which can be used to offset the utility bills, so that there is no increase in water bill on average for one and two-room HDB households after the rebates. Nevertheless, in a poll of over 1,100 citizens conducted after announcement of the water price hike, 43 percent of those polled disagreed that it was reasonable to increase water prices to fund higher costs of production and encourage conservation. Only 32 percent agreed while the rest were neutral (The Straits Times, 2017).

The second policy instrument is the mandatory water efficiency labelling. In 2009, the mandatory Water Efficiency Labelling Scheme (WELS) was introduced. The label carries different number of ticks depending on water efficiency, such that consumers can easily distinguish between water-efficient and water-inefficient appliances and fittings. The most water-efficient ones carry three or four ticks, depending on the type of appliance or fitting, whereas the least water-efficient ones carry no tick. The WELS was first applied to taps, low-capacity flushing cisterns, and urinals (Teo, 2009), and it has been expanded to dishwashers and washing machines. Mandated water-efficiency levels have increased over time such that taps with 0-ticks have been phased out. From April 2019, the PUB will mandate the sales, supply, and installation of minimum 2-tick water fittings in all new and existing premises undergoing renovation.

The third policy instrument is water conservation program. Through various educational programs and advertisements, the PUB has tried to raise awareness about the importance of and the effective ways for water conservation. For example, households are encouraged to adopt good practices that are effective in reducing water consumption, such as repairing leaks, reusing rinse water, washing utensils in a filled sink instead of under a running tap, reducing shower time, and being cognizant of the monthly water bills. The PUB also helped households reduce water usage, for example, by replacing old water closets with

more efficient ones and by installing smart shower devices to provide real-time information.

PUB introduced a redesigned utilities bill in a joint initiative with the SP Services, EMA, and City Gas from August 2016 to raise the awareness of consumers about their water, electricity, and gas usage (Goy, 2016). Unlike the old design, which only provided the consumers with their consumption compared with the national average, the new design allows consumers to view their consumption relative to the residents living in the same block and in a similar kind of housing. The new design also provides personalised tips to improve water and energy efficiency. With these initiatives, Singapore's per capita household water consumption declined from 165 litres per day in 2003 to 143 litres per day in 2017 (Public Utilities Board, 2018a). This presents a more promising picture than other major cities in the region such as Hong Kong, Taipei, and Tokyo, where per capita household water consumption was above 200 litres per day in 2016.

Singapore's success in containing water consumption owes to the households' efforts to engage in water conservation practices. According to Mr Masagos Zulkifli, Minister of Environment and Water Resources, the mandatory WELS has made households more aware of water efficient products, thus helping them reduce consumption. In 2017, automated meters installed in 500 households in Punggol helped households keep track of their daily water usage through the use of a mobile application (Tan, Audrey, 2018b). Hence, improved technology has an instrumental role to play in further reducing household water consumption in Singapore. In the light of such encouraging results, the government has revised the target for per capita household water consumption for 2030 from 140 litres per day to 130 litres per day (Yusof, 2018).

The PUB also implemented water conservation programs targeted at workplaces. In 2007, the PUB launched the Water Efficiency Fund to encourage organisations to study the best water management practices. This can be done

by hiring researchers and water experts who engage in active research within the organisation. If the organisation successfully reduces water consumption by at least 10 percent, the PUB will co-fund the project.

Since 2015, organisations that have water consumption of at least 60,000 cubic metres in the previous year are required to submit a Water Efficiency Management Plan. These organisations are strongly encouraged to implement water efficiency measures identified in the plan. To recognise the top water-efficiency performers, the Water Efficiency Awards, which evolved from the Water Efficient Building Certification, was introduced in 2017. This award is given to top performers in each of the following categories: office, retail, hotel, wafer fabrication, refinery, school, and estate.

Addressing Future Water Challenges for a Liveable and Sustainable Singapore

Since water is a scarce resource in Singapore, the management of water supply and demand is of primary importance for the sustainable use of water. Besides, water ways and reservoirs may also serve as a place for recreation and contribute to the liveability of the city. In 2006, the PUB launched the Active, Beautiful, Clean Waters (ABC Waters) Programme to revamp the blue spaces. More than 100 locations across the island have been identified as potential ABC Waters sites. As of December 2017, 36 sites had been made accessible to the public, and this project is expected to complete by 2030. In addition to providing amenity, the ABC Water sites would also promote the appreciation of reservoirs and water ways.

The water scarcity that Singapore faces may also create an opportunity. The PUB and Economic Development Board jointly lead the initiative of uniting government organisations, private companies, and research institutions to transform Singapore into a thriving global hub for research and development for wa-

ter solutions. If successful, the water solutions developed in Singapore would make Singapore more liveable and sustainable, and, at the same time, better prepared for and resilient to the perils of the future uncertainty about water. The new technologies, knowledge, and experiences generated in Singapore may also be useful to other cities around the globe, which in turn might bring about new jobs and business opportunities to Singapore.

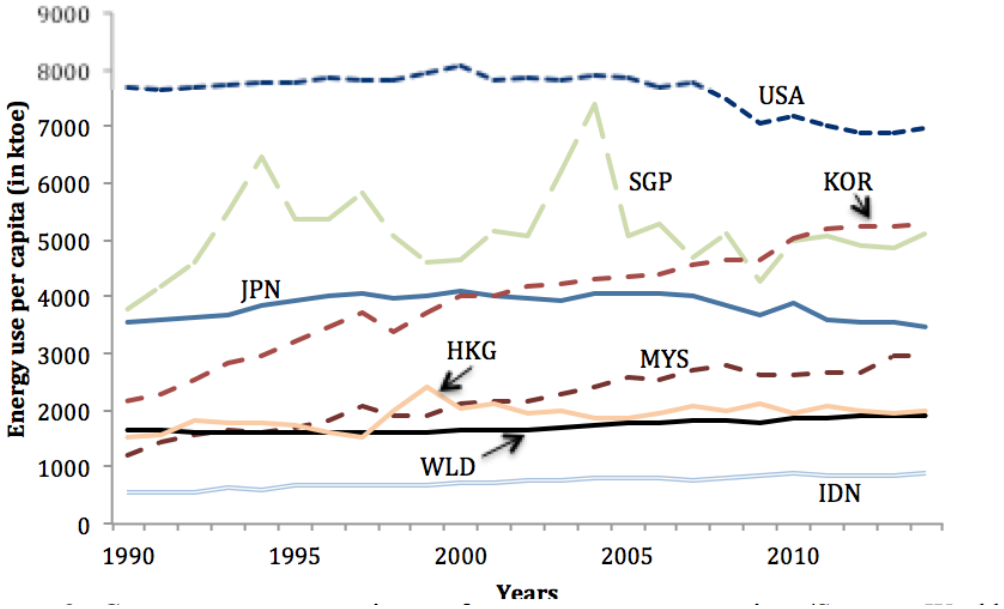
4.6 Addressing Singapore's Increasing Energy Demand

In light of rapid industrialization and an ever growing population, Singapore's energy consumption has increased by 38 percent from 10,700 kilotonne of oil equivalent (ktoe) in 2009 to 14,700 ktoe in 2017. Today, the energy consumption per capita in the island state is among the highest in Asia. It is much higher than other high income countries such as Hong Kong and Japan as well as the neighbouring countries of Malaysia and Indonesia, with the exception of South Korea. The situation is more apparent when one compares Singapore's per capita energy consumption to the world average (Figure 4.3).

Though per capita energy consumption is high in Singapore, its energy efficiency is among the highest in the world. Singapore's GDP per unit of energy use (constant 2011 PPP $ per ktoe) is not only the highest in South East Asia but also higher than some other developed economies around the globe such as Germany, Japan, and the US according to the World Development Indicators. Singapore's energy consumption depends, directly or indirectly, on fossil fuels such as petroleum and natural gas. In 2016, petroleum products and natural gas accounted for 61 percent and 9 percent of energy consumption (Singapore Energy Market Authority, 2018a). Electricity, most of which is generated by burning fossil fuels, accounts for an overwhelming majority of the rest of energy consumption, and this pattern has not changed much over the past decade.

To satisfy the large energy demand for its residents and businesses, Sin-

Figure 4.3: Cross-country Comparison of Energy Use Per Capita



Source: World Development Indicators

gapore imports fuels and fuel products from other countries. In 2017, 189.3 million tonnes of oil equivalent (Mtoe) of energy was imported, out of which 58.0 Mtoe was crude oil, 120.5 Mtoe petroleum products, 9.9 Mtoe natural gas, and 0.9 Mtoe pete and coal (Singapore Energy Market Authority, 2018a). The main sources of crude oil are mostly in the Middle East such as the United Arab Emirates, Qatar, Saudi Arabia, and Kuwait, whereas petroleum is imported predominantly from Asia, including China, India, and Malaysia.[36] It should be noted, however, that not all of the imported energy is consumed within Singapore. Singapore is the undisputed oil hub in Asia and exports 102.6 Mtoe of energy mostly as petroleum products to destinations such as Malaysia, Indonesia, and China.

Natural gas is also an important source of energy. Besides industrial demands and domestic and commercial demands for cooking and heating, natural gas also contributes to about 95 percent of electricity generation. Singapore

[36]Based on the import value reported by Singapore in the UN COMTRADE data in 2017, using as reported HS codes 2709 for crude oil and 2710 for petroleum.

has been highly dependent on Indonesia and Malaysia for import of natural gas. Therefore, to reduce dependence on the two neighbouring economies, Singapore began importing liquefied natural gas from other countries such as the United States of America, Australia, Norway, Russia, Qatar, and Brunei (Soh, 2016).

While diversification of import sources is likely to make Singapore less vulnerable to external shocks and ensure a secure and reliable supply of energy, it is critical to reduce the dependency on fossil fuels and to harness renewable sources such as solar and wind energy to enhance the sustainability of energy use in Singapore.

Since modern technologies invariably rely on electricity, its consumption deserves a special attention. The composition of electricity consumption across different sectors has been steady in Singapore. As of 2017, industry-related activities (manufacturing, construction, and utilities) consume the largest fraction of electricity (21,516 GWh) followed by commerce and service (17,804 GWh), household (7,295 GWh), and transportation (2,751 GWh) sectors. Within the household sector, the average annual household electricity consumption in private housing is 7,936 kWh, which is far more than that in public housing (4,333 kWh). Thus, there is arguably a case for advocating reduction in electricity consumption in private housing.

In the remainder of this section, we first discuss changes in Singapore's electricity market in an effort to make it more efficient. We then explore opportunities for Singapore to harness alternative sources of energy and reduce the use of fossil fuels. We also evaluate some of the energy conservation and emission reduction policies adopted by the government to make energy use of the city-state more sustainable.

Singapore's Electricity Market and its Evolution over Time

Singapore's experience with electricity dates back to the early 20th century. With the opening of the Mackenzie Road Power Station in 1905, electricity was provided only to limited areas in the central part of Singapore. In 1927, St James Power Station began generating electricity with a 2 MW steam turbo-alternator set, and the consumer base also increased. For example, between 1920 and 1930, the number of consumers connected to mains electricity went up from 1,452 to 13,100. Both the consumer base and generation capacity have continued to grow over time with a notable exception of the period around the Second World War. After the war, the first 25 MW generator in Pasir Panjang was placed in service in 1952. By 1960, combined generation capacity of Pasir Panjang and St James Power Stations reached 188MW (Public Utilities Board, 1985).

In 1965, the then Prime Minister Lee Kuan Yew opened a new power plant in Pasir Panjang to further increase the generation capacity. Subsequently, Jurong, Senoko, and Pulau Serava power stations opened in the 1970s and 80s. Singapore also entered into a deal with Malaysia in 1986 where it could share electricity with its neighbouring country during power outages. In 1995, PUB's electricity and piped gas undertakings were corporatised to liberalise the market and allow competition. Opening up the market not only resulted in increased efficiency but also complemented PUB's investments in infrastructural needs of the energy sector and was a major precursor to Singapore's eventual privatisation of the energy sector. In 1998, the Singapore Electricity Pool was formed to allow competitive price bidding among the power generation companies. In 2001, two major developments related to the energy sector took place; (i) electricity generation was separated from transmission and distribution functions, and (ii) the Energy Market Authority (EMA) was set up to further monitor the liberalisation process and to ensure a dependable and safe energy supply. About

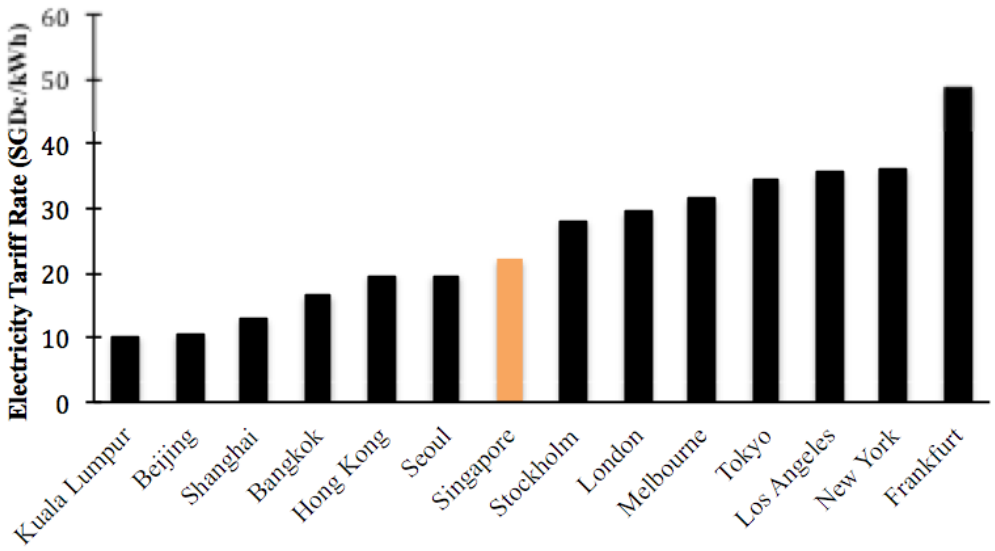
250 business consumers with an electricity demand of more than 2 Megawatt (MW) were allowed to choose their own suppliers. In 2003, the National Electricity Market of Singapore (NEMS) opened up for trading and retailers could now buy electricity in bulk from the wholesale market to supply to consumers. In 2006, large consumers whose average monthly electricity consumption was 10,000 kWh and above became eligible to switch to a retailer of their choice.

Since the start of the NEMS, generation companies have been obliged to place bids every half an hour to sell electricity in the wholesale market. The SP Group (SP Services) and retailers buy electricity in bulk from the wholesale electricity market, following which the SP Group, through its member SP PowerGrid, transmits the electricity generated to its consumers. An analysis of NEMS by Chang (2007) suggests that the NEMS is quite competitive, even though the generation market is highly concentrated.

Until 2017, households and small business consumers could buy electricity only from SP Services at the regulated tariff. From 2018, the Open Electricity Market has been rolled out in phases and these relatively small entities now have the right to buy electricity from a retailer of their choice (non-contestable consumers) or directly from the wholesale market (contestable consumer). By building up the generation capacity, which is over 13,614.4 MW in 2018 (Singapore Energy Market Authority, 2018a), and by liberalising the electricity market, Singapore managed to provide electricity at an affordable price through increased capacity and competition. The prevailing tariff rate for electricity in Singapore is 25.52 cents per kWh (Singapore Energy Market Authority, 2019), which is higher than some cities in other Southeast Asian countries but considerably lower than many other cities in Europe and the United States (Figure 4.4).

The brief history of Singapore's electricity sector we discussed above offers a great story of transforming a primitive market into one that was liberalised in an orderly fashion through a well-planned process. The gradual liberalisation of the electricity sector has made energy sector become more competitive and

Figure 4.4: Comparison of Electricity Tariff Rates across Cities around the World based on Electricity Prices in 2017



Source: The Lantau Group.

efficient without disrupting the steady supply to households and businesses. Furthermore, the introduction of the Open Electricity Market provided consumers with an alternative, giving them an opportunity to use electricity - a necessity in a liveable city - at a more affordable rate. Further, the Open Electricity Market allows the consumers to choose 'greener' options. For example, ES Power offers 100% Carbon Neutral Electricity options,[37] whereas Sunseap offers 100% solar energy option.[38] Therefore, the Open Electricity Market can also support the choice that Singaporeans make for sustainable use of energy.

Harnessing Renewable Sources of Energy

As we have seen above, Singapore primarily depends on import of fossil fuels to meet its energy demand. Though a large amount of energy can be generated by burning fossil fuels, it entails emissions of various air pollutants and contributes

[37]https://oem.espower.com.sg/. Accessed on 8 April 2019.
[38]https://www.sunseap.com/. Accessed on 8 April 2019

to global warming through the emission of carbon dioxide. Further, fossil fuels are non-renewable. Therefore, it is imperative that Singapore harnesses alternative, renewable sources of energy to meet the energy demand of its residents and businesses sustainably.

Currently, Singapore's use of renewable energy is mostly limited to solar power, with its contribution to electricity generation being less than 1 percent. With an average annual solar irradiance of 1,580 kWh/m^2/year, Singapore has tremendous potential to expand the use of solar PV generation since it receives 50 percent more solar radiation than temperate countries (Singapore Energy Market Authority, 2018b). Thus, even though solar energy is largely untapped at the moment, it can potentially help Singapore attain a number of important objectives. First, solar energy is renewable and solar PV generation entails virtually no emission of carbon dioxide once the solar panels are installed. Therefore, the use of solar energy significantly improves the environmental sustainability of the city-state. Second, by reducing the reliance on import of fossil fuels, Singapore will become less vulnerable to the fluctuations in oil and gas markets. Third, the solar energy can help fulfil peak demand of electricity since the maximum output of solar energy occurs during the afternoon, which coincides with the time of peak energy use.

Despite these potential benefits, Singapore's ability to scale up the installation of solar panels is constrained by its land area. In spite of this problem, there has been considerable increase in solar PV from 25.7 MW in 2014 to 112.3 MW in 2017. Further, the number of grid-connected solar PV installations increased noticeably from 637 in 2014 to 2117 in 2017. The EMA aims to further raise the adoption of solar power to 1 gigawatt-peak (GWp) in the next decade, which will help Singapore achieve the target of reducing emissions intensity by 36 percent from the 2005 level (Singapore Energy Market Authority, 2018b).

While geothermal and hydropower are not viable modes of electricity generation in Singapore, tidal and wind generation have been explored. Even though

the potential of these sources to generate power is limited in Singapore, they can complement solar power, as they are able to generate power at night or under the cloud.

Singapore's first tidal turbine system, planned and constructed by the Energy Research Institute of Nanyang Technological University, was built off Sentosa in 2013. Though the majority of the sea space in Singapore is used for anchorage, ports, and shipping lanes, there are plans to construct around 150 to 200 tidal turbine systems over 15 years, which would generate 200 MW of power (Ee, 2013). In 2017, Singapore's first long-span wind turbine was installed at Semakau Landfill, and it can generate sufficient energy to power around 45 four-room HDB units per year (Channel News Asia, 2017b). The power generated from the wind turbine is connected to a hybrid microgrid, which can consolidate power generated from other sources such as solar, tidal, diesel, and power-to-gas technologies and collectively supply enough power for 1,000 four-room flats (Wong, 2016). In the first phase of the project, a microgrid facility with more than 4,500 m^2 of photovoltaic cells and a large-scale energy storage system was installed.

While the technologies discussed above are still needed to be tested and calibrated, energy generated from solar, wind, and tidal power and combined through microgrid may have the potential to enable Singapore to reduce dependency on import of fossil fuels and make its electricity supply more sustainable.

Promoting Energy Efficiency

The Singaporean government has taken several policies to increase the awareness of and promote the practice of energy conservation among households. One example is the Project Carbon Zero, a competition held in 2009 among primary- and secondary-school students, and its objective was to see whether children could nudge their parents to change their energy consumption pat-

terns. The energy consumption of the participating households was monitored over the baseline period (January-April) and then during the competition period (May-August). If the average energy consumption in the competition period was less than that in the baseline period by more than 10 percent, children were awarded with a certificate and a S$10 book voucher. There were also rewards for the participating schools and the best performing students. Agarwal et al. (2017) found that households within 2 kilometres of the participating schools consumed 1.8 percent less electricity at the block level than those residing outside the 2-kilometre school zone. This indicates that children can act as an agent of change in household behaviour. He and Kua (2013) showed that a combined use of leaflets and stickers used under the Eco-living Program – implemented in the Hong Kah North Residential Council in the southwestern part of the city – resulted in a 15.8 percent decrease in electricity consumption between October 2010 and July 2011. Besides these programs, the NEA has rolled out the Save Energy Save Money initiative to encourage households to cultivate energy-saving habits, such as switching off appliances at the power socket, switching off the heater after use, using more energy-efficient appliances, and using fan instead of air conditioner (National Environment Agency, 2018a).

To help consumers make informed decision, a Mandatory Energy Labelling Scheme (MELS) was introduced in 2008 for regulated goods (air-conditioner, refrigerators, clothes dryers, televisions, and lamps). Similar to the WELS, appliances are given different numbers of ticks according to their energy efficiency under the MELS. The Minimum Energy Performance Standards (MEPS) implemented in 2011 has complemented the MELS by prohibiting the sales of appliance models that did not meet the minimum specified energy efficiency level. The increase in energy efficiency through the implementation of the MELS and MEPS not only contributes to the sustainable use of energy but also reduces the households' monthly electricity bills.

Guidelines for energy efficient practices are in place not only for households

but also for energy intensive companies. Since 2013, energy intensive companies are required under the Energy Conservation Act to register with the NEA and implement mandatory energy management practices. Upon registration, companies must i) appoint an energy manager, ii) monitor and report energy use and greenhouse gas emissions annually, and iii) submit energy efficiency improvement plans annually (National Environment Agency, 2018b).

Both private and public sector entities have also been encouraged to improve energy efficiency through various programs. For example, the Energy Efficiency National Partnership, a voluntary program implemented in 2010 and targeted towards businesses consuming a large amount of energy, helps these businesses increase their long-term competitiveness through learning network activities, provision of energy-efficiency related resources, and incentives and recognition (National Environment Agency, 2019). The NEA also provides the Energy Efficiency Fund to help businesses become more energy efficient. Under the Public Sector Taking the Lead in Environmental Sustainability initiative, public sector agencies have been encouraged to implement environmental sustainability measures that encompass energy efficiency, water efficiency, and recycling (National Environment Agency, 2018c).

Overall, Singapore appears to have taken some steps towards more sustainable energy use. Consumers in Singapore now have an opportunity to make greener choice for electricity supply with the liberalisation of electricity market. Various policies have been put in place to promote efficient use of energy in household, private, and public sectors. Nevertheless, given that Singapore has among the highest energy consumption per capita in the world and the use of renewable energy remains very limited, there remains a large room for improvement. To ensure its environmental sustainability, Singapore will have to improve energy efficiency, use more renewable sources, and reduce its carbon footprint.

4.7 Moving Forward

Singapore has achieved a truly remarkable transformation since its independence in 1965. At the time of independence, Singapore's public policy primarily focused on meeting the pressing needs of the time. However, policymakers in Singapore also had a long-term perspective. The presence of good planning, which is particularly apparent in land use, transportation, and water policies, helped Singapore achieve sustained economic growth for five decades with little interruptions in between. Further, even though Singapore's policies have been primarily directed towards the promotion of economic growth, some considerations have always been paid to the living environment (Quah and Soh, 2014). As Singapore's standard of living goes up, the emphasis of public policies has shifted towards the enhancement of the city-state's sustainability and liveability, particularly over the past decade. We have provided an overview of some of the important policies and their historical backgrounds. In this section, we draw some lessons from these policies and discuss the challenges and opportunities that may lie ahead of us.

Incentive versus Normative Messages for Sustainable Policies

Singapore has implemented various measures to provide relevant information to the consumers through labelling and certification such as the Green Mark Scheme, WELS, and MELS, which can be expected to help people make informed choices. Another important feature of Singapore's policies is the extensive use of economic incentives. As we have seen, various incentive policies have been used in land use, transportation, water, waste management, and energy policies. Among all, the extensive use of road pricing is unique to Singapore and particularly noteworthy. Singapore's policy is also notable in its flexibility. The Singaporean government quickly tweaks its policies as needed. This is important for the success of policy, because the behavioural response is

generally difficult to anticipate perfectly. Therefore, even when there are some loopholes in the policy, Singapore tended to plug them swiftly.

While economic incentives can be a powerful policy instrument, incentives alone may not be sufficient. If incentive policies are not implemented appropriately, they may convey a wrong signal to the public. To make this point, take as an example a randomised field experiment involving child-care centre in Israel by Gneezy and Rustichini (2000). They studied the impact of the introduction of fine for parents picking up their children from child-care centre after closing time. They found that the parents in the treatment group, who are subjected to the fine, were actually more likely to pick up their children late than those in the control group, who did not face the fine. Further, the number of late-coming parents in the treatment group did not reduce even after the fine was removed. One plausible explanation is that the social norm may change with the introduction of the fine. That is, parents may feel more justified in picking up their children late as they now pay for the service provided by the caregivers who do not have to work for free. Further, the new social norm seems to persist even after the fine was removed.

While Gneezy and Rustichini (2000) offer a cautionary tale of economic incentives, its relevance to sustainability policies in Singapore is unclear. Nevertheless, we argue that providing a clear normative message is potentially helpful. In a randomised experiment conducted with 1,000 HDB households in Ang Mo Kio in 2016, households that received normative messages about water usage, which either appeal to the social norms by highlighting how the household compares with others in the neighbourhood or to the moral by highlighting the importance of doing right. In this study, households that received normative messages significantly reduced water usage. Further, adding economic incentives to conserve water had no additional impacts on water conservation efforts (Leong and Goette, 2019).

This, of course, does not mean that normative message would always work

or be more effective than economic incentives. For example, in a randomised study of households in the Kansai region of Japan, Ito et al. (2018) found that the economic incentives, which charge a high electricity tariff during the critical peak-demand hours, significantly reduced electricity demand during the treatment hours. Further, the economic incentives also appear to have induced treatment households to adopt more energy-saving behaviour, such that their energy consumption outside the peak-demand hours was also lower than the control households, and the treatment impact was lasting. On the other hand, moral suasion treatment, which provides consumers with a message describing the need for energy conservation during the critical peak-demand hours, reduced the energy consumption only marginally and insignificantly and its impact was short-lived.

The discussion above, therefore, suggests the importance of exploring both economic incentives and normative messages to raise the sustainability of the city-state, since they can potentially complement each other. Rather than looking at normative messages and economic incentives as substitutes for each other, the Singaporean government should exploit the complementarities available in these two kinds of policy design. Fully exploring both options is also important because the details of implementation is likely to matter. For example, economic incentives can be implemented under the names of prices, taxes, fees, tariffs, fines, charges, and so on. In terms of the monetary transaction, they may mean the same thing, but the message that they convey can be very different. Similarly, how well normative messages work depends on how well these messages are crafted as well as how they are conveyed. Indeed, Singapore also implemented various programs to send normative message to households and businesses in addition to economic incentives. Experimental economics approach can elucidate how people respond to different types of policies and help policy-makers find a best mix of economic incentives and normative messages (See, for example, Lee and Tan (2019)).

Important Areas of Challenge

While there are many elements of success in Singapore's sustainability policy, all areas we reviewed in this paper – land use, transportation, water, waste, and energy – are likely to continue to pose important challenges in the coming decades. In particular, two issues stand out as the areas that need more work. First, Singapore would need to make more efforts to contain the emission of wastes to bring it down to the level of other Asian cities. To this end, it would be important to take more measures to raise the awareness of the importance of 3Rs and make it easier to participate in recycling. For example, unlike some other cities, it is hard to come across recycling bins for recyclables such as plastic bottles and cans in the streets and the public spaces of Singapore. Cutting the trouble of travelling for recycling by adding the necessary infrastructure would be a first step to facilitate the participation of the public in recycling.

Second, Singapore's heavy reliance on import of fossil fuels will need to be addressed. As with water, Singapore's dependence on import of fossil fuels is a potential source of vulnerability and goes against the sustainable use of energy. For these reasons, it is imperative that Singapore further pushes for energy efficiency and use of renewables. Particularly for energy efficiency, the efforts by the private sector are indispensable, because the industrial-related and commerce and services-related sectors account for, respectively, about 65.7 and 11.5 percent of the total final energy consumption in 2016 (Singapore Energy Market Authority, 2018a).

It is important to note that the push for energy efficiency or better environmental performance in general does not necessarily harm the businesses. Clearly, efficient use of resources, including energy and water, makes business sense. Furthermore, better corporate image can be attained by improving the environmental performance. Therefore, energy efficiency and better environmental performance do not need to come at a sacrifice of business.

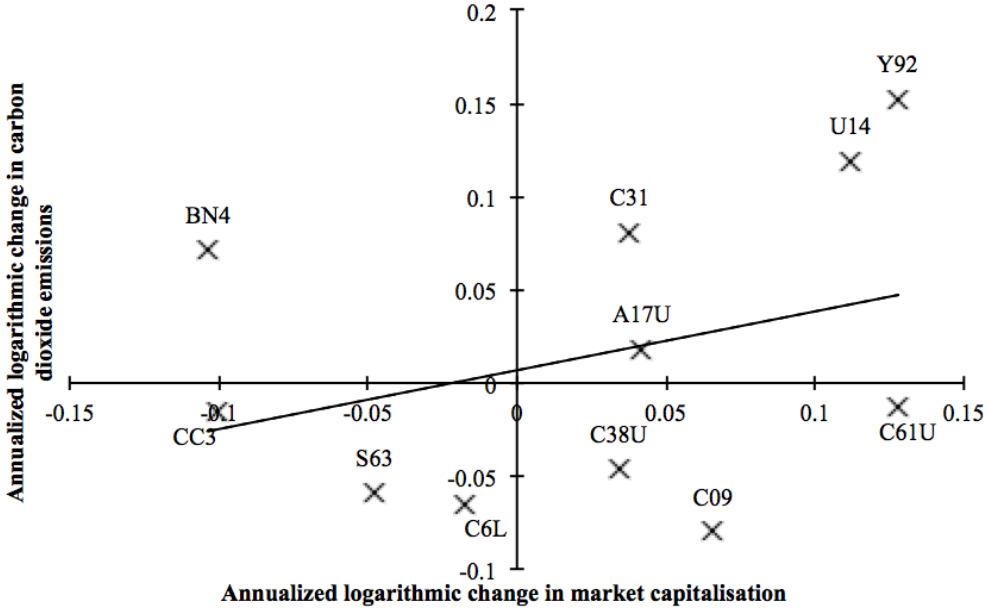
To highlight this point, we compiled a dataset for the companies underlying the STI Index, which tracks the performance of the top 30 companies listed on SGX using published sustainability reports and other sources. We then looked at the relationship between the average yearly changes in market capitalization and changes in environmental performance indicators such as electricity usage, water usage, and carbon dioxide emissions between 2013 and 2017. Because the sustainability report is not mandatory and “comply or explain" policy was only introduced in 2016, we only have data for 11-13 companies, depending on the environmental performance indicator. Therefore, our analysis is limited by the data availability.

Subject to this caveat, when the company becomes larger in terms of the market capitalization, electricity usage, water usage, and carbon dioxide emissions tend to increase during the observation period. Figure 4.5, for example, shows that there is a positive correlation of 0.33) between the change in market capitalisation and change in carbon dioxide emissions. We also found that the change in market capitalization is positively correlated with the change in water usage by 0.42 and with electricity usage by 0.10.

This result is not surprising. Nevertheless, there are companies that have achieved growth in market capitalization and improved the environmental performance between 2013 and 2017. In particular, City Development (C09), a property and hotel conglomerate engaged in real estate development, is worth highlighting. It has reduced water usage, electricity usage, and carbon emissions by 9 percent, 5 percent, and 8 percent annually during our observation period, while achieving an average annual increase of nearly 7 percent in market capitalization. Besides these achievements, the City Development has won a number of environmental awards over the last decade and achieved the ISO 140001 certification for all functions at headquarters in 2008.

Clearly, these achievements cannot be attributed to a factor that is specific to the real estate sector, because other major real estate and property companies

Figure 4.5: Changes in Market Capitalisation and Changes in Carbon Emissions for Companies in STI Index



such as CapitaLand (C31), Ascendas Real Estate Investment Trust (A17U) and UOL Group (U14) have expended more energy, water, and electricity at the time of their growth in market capitalization. Instead, we argue that the City Development's environmental achievements can be attributed to its commitment to "Environment, Social and Governance" since 1995 when it established CSR-centric vision and adopted business model of "Conserving as we Construct".

Obviously, the case of City Development is simply an anecdote and it remains to be seen whether other businesses can simultaneously achieve the growth in business and improvement in environmental performance. Nevertheless, there are other success stories of doing well by doing good elsewhere (e.g., Laszlo (2008)). Thus, policies to encourage such business models would be conducive to Singapore's journey towards a sustainable and liveable city. For example, the government can implement standard market instruments such as emissions taxes, tradable permits, and subsidies for emissions reduction. In fact, Singapore just implemented a carbon tax in 2019 for large emitters – mainly from

the petroleum refining, chemical, and semiconductor sectors – at the rate of $5 per tonne of emissions. This will go up to between $10 and $15 per tonne of emissions by 2030, but there is a scope for increasing the coverage of emitters and tax rates. Besides market instruments, the government can also implement policies to promote the sharing and transfer of new knowledge, management, and technologies across firms.

Potential Opportunities for Singapore

Singapore has great potential to lead the world in transforming a city to become more sustainable and liveable and in creating a great place to live, work, and play. Singapore has been dubbed as a place where “East Meets West" and its culture is a confluence of various Asian and European cultures, which has allowed the country to take advantage of the strengths of both. As a young nation with an effective government and a good pool of talent, Singapore continues to be well positioned to test and adopt new ideas, technologies, and policies to tackle new challenges. In particular, Singapore can fruitfully take advantage of automation and artificial intelligence (AI) to optimise the allocation of resources to make the city simultaneously more liveable and sustainable.[39]

Transportation is a good example. Private cars that are used for commuting are typically driven only a few hours a day at most. During the rest of the day, they simply occupy parking lots. Therefore, this leads to an inefficient use of space and cars. While public transportation does not suffer from this issue, it can only serve the routes that have sufficient ridership. Therefore, if self-driving cars can be rented out to end-users during their idle time, both space and cars can be used more efficiently. Further, if the rides among end-users can be shared, energy can be more efficiently used to move people. These possibilities would also help reduce the need to own a car.

[39] Singapore ranks 1st together with Australia and Sweden in Technological Readiness Ranking for 2018-22 (Economist Intelligence Unit, 2018).

When the technology matures and precision of driving improves, the efficiency of road transportation may improve. In a situation where pedestrians are separated from motor vehicles, all cars on the roads are AVs, and they can communicate with each other in an orderly manner, vehicles would take the optimal route and even traffic lights may become unnecessary. In such a situation, AVs would be able to drive faster and at the same time safer than now. Since Singapore is small and densely populated, the time may come when it makes economic sense to build roads on which electric vehicles can be recharged while driving (Sweden already has an electrified road. Wireless charging is also technologically feasible). This in turn makes it easier to put smaller and lighter cars on the road as they do not need a high-capacity battery. Further, with the advancement of drone technology, air space can be used for transportation of goods (and possibly people), which in turn can potentially mitigate the space constraint on the ground.

Together with the accumulation of data, AI can often outperform human experts in prediction. This, in turn, allows us to facilitate efficient use of resources. For example, inventory, which does not produce anything on its own, can be managed efficiently with the help of AI. AI can also enable better demand prediction and supply chain management, which will enable firms to integrate retail sales and logistics better. As a result, the time, energy, and cost needed to deliver goods from producers to consumers can be saved. The potential gains from automation and AI discussed above are admittedly speculative and there are safety, legal, and other issues to be addressed. Nevertheless, these gains are not unimaginable and, if realised, may bring about a significant positive impact on a space- and resource-constrained country like Singapore.[40]

The space constraint Singapore faces also creates an opportunity to explore

[40]While the discussion on the demographic challenges of Singapore is beyond the scope of this paper, it is worth noting that Singapore's total fertility rate was 1.14 in 2018, among the lowest in the world. The use of automation and AI can both be spurred by and help mitigate the issue of ageing society (for a related discussion, see Acemoglu and Restrepo (2018)).

offshore technologies. For example, an offshore floating solar panel system, which will be able to generate 6,388 MWh of renewable energy annually, is already being built (Tan, Sue-Ann, 2018). Lim (2017a,b) even argue for building nuclear power plants on floating platforms. Even though the scalability of these ideas within Singapore's water may be limited given Singapore's busy maritime environment, new types of offshore technologies can simultaneously address Singapore's energy issue and add to Singapore's competitive advantage.

While this paper has focused on domestic issues, Singapore will not be able to escape form the challenges of climate change. Indeed, Singapore has become increasing wary of this fact as can be seen from the 2019 National Day speech by Prime Minister Lee Hsien Loong (Prime Minister's Office, Singapore, 2019). With about 30 percent of the island less than 5 metre above the mean sea level (Chang, 2019), Singapore is particularly vulnerable to the sea level rise, which is estimated to rise by 1 metre by 2100.

To cope with such serious long-term threats, Singapore is exploring options such as building polders or connecting islands to create freshwater reservoirs. This can be viewed as an opportunity to improve the island's infrastructure and potentially make Singapore a model of resilient city that other cities could follow. Obviously, such options are costly. Prime Minister Lee Hsien Loong estimates that it will cost $100 billion or more over 100 years to protect the country against rising sea levels. Despite the high cost and long time horizon involved, Singapore is apparently confident in dealing with the challenge of climate change. As Prime Minister Lee Hsien Loong puts it in his speech (Prime Minister's Office, Singapore, 2019), "In Singapore, for long-term problems, we can make long-term solutions. Not everywhere, but in Singapore, yes, we can."

In conclusion, Singapore is likely to continue to face challenges in land, transportation, water, waste, and energy issues in the future because of its inherent constraints of small size and little resources. Nevertheless, Singapore has an excellent record of accomplishment of addressing these challenges and great

potential to become an exemplar city of sustainability and liveability.

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Appendix

A Documentation of Error Rates in SMS

SMSes were sent to households in the CCT and SMS treatment arms in Bengali both in the form of text messages and voice on a weekly basis, and this process took place in the week following intervention school days and lasted from Monday to Wednesday. This was done manually in 2017. However, there were operational difficulties such as the departure of a key operational personnel and nationwide teacher strikes which led to irregular working hours in schools. This resulted in some lapses in the first few weeks of Phase 1, 2018. The lapses include the replacement of text SMSes with informal phone calls until February and the omission of voice SMS until March. We also discovered that some of the SMSes sent to the study participants contained errors.

Once these issues were discovered, we conducted an audit to assess the prevalence of errors by checking the SMS against the attendance records in one of the subsequent weeks in Phase 1, 2018. Based on this audit exercise, the error rates in weekly attendance information, weekly transfer amount, and current balance were estimated at 3.9 percent, 4.2 percent, and 5.9 percent, respectively. We found no significant difference in the error rates across different treatment arms. This, in turn, suggests that the estimated effects of our treatments, particularly SMS treatment, may have been attenuated because of the errors in the SMS information.

To adequately address the above-mentioned issues, we introduced an automated process of sending SMSes from Phase 2, 2018, which increased the reliability of the information in the SMS. As Table 1.2 shows, the impact of the SMS treatment in Phase 2, 2018 is highly statistically significant and larger than previous phases. These results are indeed consistent with our conjecture that the improved reliability of the SMS information in Phase 2, 2018 increased the

effect of the SMS treatment.

B Measuring Consumption

Instead of using a full consumption module that takes a long time to complete, we chose to collect consumption expenditures for a small number of consumption items that have high predictive power for total consumption because of the limited budget for data collection. To determine the consumption items to collect, we used the consumption data from the skills training program, which was also performed in the Gaibandha district. The following items were found to have a high predictive power of the total consumption in a linear regression ($R^2 = 0.929$): rice, chicken, fish, okra, onion, and cigarettes consumed in the past seven days, and energy, clothes and footwear, soap or washing product, hair cut and other personal services, and cosmetic articles consumed in the past one year. We collected these consumption items in the baseline survey and used the regression coefficients and household size to derive the predicted annual household consumption per capita, which is used as a measure of standards of living.

C Further Discussion on Cost-Effective Analysis

In this section, we consider the choice of cost-effective intensive margin. Because the difference in the impact of Gain and Loss treatments on the attendance is similar, we use the following model that is quadratic in the transfer amount τ_{it} to focus on the intensive margin of the CCT transfer.

$$\mathrm{Y_{it}} = f_0 \mathrm{CCT}_i + f_1 \tau_{it} + f_2 \tau_{it}^2 + \beta \mathrm{SMS}_i + \alpha + \gamma X_i + \theta Z_i + \phi D_t + \varepsilon_{it}, \qquad \text{(A1)}$$

where $\mathrm{CCT}_i = \mathrm{Gain}_i + \mathrm{Loss}_i$ is an indicator that individual i is either in the

Gain or Loss treatment. The transfer amount τ_{it} is the transfer individual i receives, which is zero if $\text{CCT}_i = 0$ and 10, 20, or 30 otherwise depending on the phase and subtreatment. We denote the expected attendance in the absence of any intervention for individual i in day t by $A_{it} \equiv \alpha + \gamma X_i + \theta Z_i + \phi D_t$ and interpret $f(\tau) \equiv f_0 + f_1\tau + f_2\tau^2$ as the attendance impact of a CCT intervention with a transfer of τ taka/day. Based on the regression estimates from eq. (A1), we predict $f(\tau)$ (full regression results available upon request). Figure A1 shows the graph of the predicted value of $f(\tau)$ and its 95 percent confidence bounds, which clearly shows the diminishing marginal impact. As the figure indicates, the transfer amount has to be slightly above 10 taka/day to have a significant impact on attendance. The figure also indicates that the marginal effect becomes zero around 36 taka/day. Note, however, that τ takes values between 10 taka/day and 30 taka/day and thus the estimates outside this range may not be very reliable in our data. The regression based on eq. (A1) also allows us to predict A_{it}. Even though it is not bound to be on the unit interval, 99.8 percent of observations are within the unit interval. The mean and median of A_{it} are both around 0.53, which is very close to the control mean reported in column (1) of Table 1.2. The dotted line in Figure A2 represents the kernel density estimate of A_{it}.

Let us now find the most cost effective amount of transfer τ^* as a function

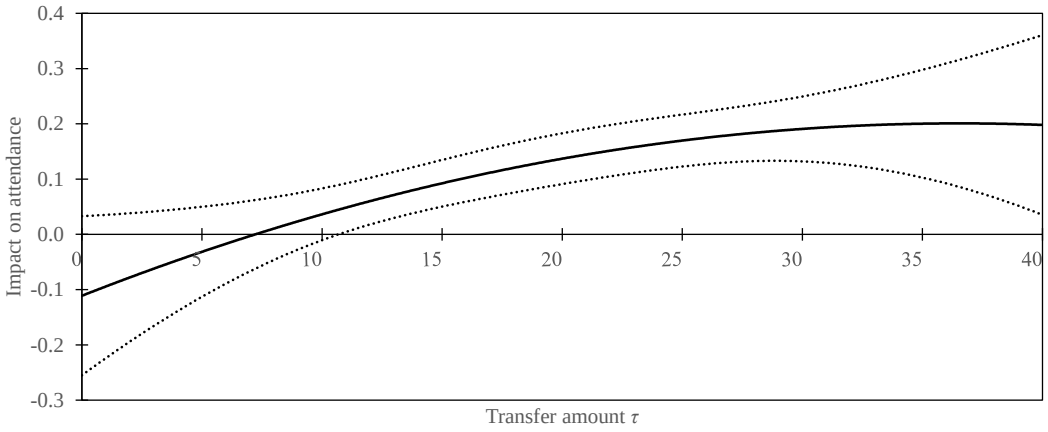

Figure A1: The Estimated Attendance Impact of CCT with Daily Transfer τ.

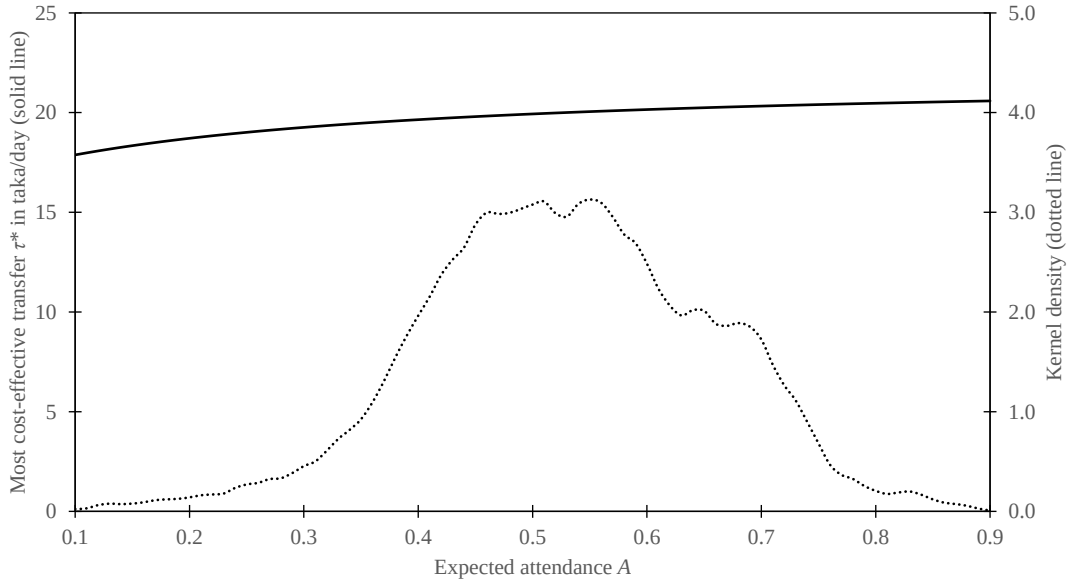

Figure A2: The Most Cost-effective Transfer τ^* (solid line) and the Kernel Density Estimate of the Expected Attendance A in the Absence of Intervention (dotted line) as a Function of A.

of A. Notice that the non-transfer cost of the program does not vary with τ. Since there are 155(=(60+50)/2+50+50) intervention days across the two cohorts, the non-transfer cost for each student is $C = 188.65/155 = 1.22$ taka/day. Now, notice that the attendance in the presence of the CCT program is given by $A + f(\tau)$. Therefore, the expected daily transfer cost is $(A + f(\tau))\tau$ per student and the expected total program cost is $(A + f(\tau))\tau + C$. The attendance impact per program cost is therefore maximized when the following expression is maximized:

$$\frac{f(\tau)}{(A + f(\tau))\tau + C}$$

Taking the first order condition and rearranging the terms, we see that τ^* is implicitly given by the following expression:

$$f'(\tau^*)(A\tau^* + C) - f(\tau^*)(A + f(\tau^*)) = 0$$

The solid line in Figure A2 shows the most cost-effective transfer amount τ^* as a function of A. While the analysis above ignores spillover effects, most

of the arguments above will hold so long as the spillover effects are uniform across individuals, which is likely to be the case. However, the estimated value of A may be biased upwards since the students in the regression analysis are all affected by spillover effects.

D Supplementary Tables and Figures

Table A1 shows the sample size by cohort, grade and gender. Tables A2 and A3 perform balance checks for the old and new cohort, respectively. Table A4 checks afternoon attendance for the subsample of person-day records where the child was present in the morning. Table A5 shows the impact estimates from the pure experimental design, without controlling for fixed effects and inclusion of unbalanced covariates at the baseline. It additionally shows the p-values from multiple hypothesis testing using Westfall-Young correction. Table A6 shows the impact estimates for students who were part of the intervention throughout the entire two year duration. Table A7 checks for whether there is differential attrition across the four treatment arms. Table A8 shows the pre-intervention attendance trends for some old-cohort students (grade 6 in 2016) and all new-cohort students. Table A9 performs a robustness check by clustering errors at the individual, school, grade, school-grade, and section levels. Table A10 shows the impacts of the interventions by phase. Table A11 shows the differential impact on “High" [H] and “Low" [L] CCT subtreatments in the second phase of 2018. Table A12 looks at treatment heterogeneity by pre-intervention attendance trends. Table A13 studies the differential impact between boys and girls in the sample. Table A14 looks at impact heterogeneity across education levels of the head of household. Table A15 analyzes the heterogenous impact of treatment based on the distance from home to school. Table A16 looks at whether the impact estimates vary across different levels of household consumption per capita. Table A17 checks for whether remembering CCT and retaining SMS

have any positive impact on attendance. Table A18 looks at spillover across sections with participating and non-participating students. Table A19 identifies the impact of our treatment assignment on the post-intervention school enrollment rate in 2019. Table A20 performs a heterogeneity analysis by grade on the incidence of early marriage for females. Finally, Table A21 analyzes the impact of the intervention on the mathematics test scores of students.

Table A22 shows the classification of states based on the minimum legal drinking age as of 2005-06. While Table A23 shows the prevalence of intimate partner violence based on the availability/non-availability of alcohol across different states in India, Table A24 does the same based on the variation in minimum legal drinking age across states. The first stage results for the impact of alcohol ban on alcohol consumption are given in Table A25 while Table A26 shows the first stage results for the impact of minimum legal drinking age on drinking habits. Table A27 looks at the impact of alcohol consumption on incidence of intimate partner violence for the entire sample and includes women who have had multiple marriages. Table A28 analyzes the impact of alcohol consumption on different facets of physical violence, where the outcome variables are binary. Table A29 checks whether the results are driven by differences in women's gender attitude between states where alcohol is allowed and alcohol is banned. Table A30 conducts a heterogeneity analysis based on the structure of the house that the couple lives in. Table A31 performs a heterogeneity analysis based on the individual's past exposure to domestic abuse and Table A32 looks at the differential impact of alcohol consumption on incidence of intimate partner violence based on the level of education disparity between the wife and her husband.

Table A33 shows the state wise implementation of the mid day meal program in India by year and month. Table A34 analyzes how confidence of households in schools is correlated with exposure to the mid day meal program. Table A35 shows the impact of the mid day meal scheme on educational expenditures using

household fixed effects. Table A36 analyzes the impact of the mid day meal on educational expenditures at the intensive margin. Table A37 performs robustness check by dropping households who have migrated to the current location in the last three years. Table A38 clusters standard errors at the state level. Table A39 performs a placebo test to further lend validity to our point estimates. Table A40 looks at the probability of children attending a government or a private school across different consumption quartiles. Table A41 performs a heterogeneity analysis by place of residence (rural/urban) on the impact of mid day meal on school fees. Table A42 looks at the probability of children attending a government or a private school in rural and urban areas.

Table A1: Sample Size by Cohort, Grade, Gender

		Grade				
Cohort		6	7	8	9	Total
Old	Male	157	40	—	—	197
	Female	163	40	—	—	203
	Total	320	80	—	—	400
New	Male	—	—	105	100	205
	Female	—	—	101	93	194
	Total	—	—	206	193	399

Note: Two male students from the old cohort repeated grade 6 in 2018.

Table A2: Summary Statistics and Balance Check for Old Cohort

	Gain (1)	Loss (2)	SMS (3)	Control (4)	Overall (5)	Orthogonality† (6)
Father has at least primary education	0.420	0.450	0.410	0.440	0.430	0.939
Mother has at least primary education	0.420	0.400	0.380	0.420	0.405	0.928
Father has at least secondary education	0.080	0.100	0.080	0.070	0.083	0.900
Mother has at least secondary education	0.030	0.060	0.030	0.080	0.050	0.323
Household size	4.840	4.680	4.860	4.780	4.790	0.740
Male members in household	2.440	2.350	2.470	2.410	2.418	0.862
Female members in household	2.400	2.330	2.390	2.370	2.372	0.964
Owns residential land	0.940	0.980	0.990	0.980	0.973	0.289
Owns agricultural land	0.290	0.250	0.340	0.230	0.278	0.331
Has television or radio	0.350	0.410	0.450	0.480	0.423	0.267
Has a bicycle	0.310	0.400	0.340	0.370	0.355	0.580
Has a tube well	0.950	0.940	0.950	0.970	0.952	0.738
Has an electric fan	0.710	0.690	0.730	0.770	0.725	0.613
Weight of the child	35.510	35.830	36.520	36.090	35.987	0.790
Height of the child	55.920	54.870	56.430	56.080	55.825	0.347
Standardized test score	0.000	0.101	0.115	0.000	0.054	0.780
Observations	100	100	100	100	400	0.895

Note: The first four rows are dummy variables that take a value of 1 if the male household head has at least primary and secondary education and the female household head has at least primary and secondary education, and 0 otherwise, respectively. Ownership of assets (agricultural land, radio/television, bicycle, tube well, electric fan) is a binary variable that takes a value of 1 if the household owns the asset, and 0 otherwise. The weight of the child is measured in kilograms, and the height of the child is measured in inches. Test scores are normalized relative to control mean and standard deviation. Column (5) shows the mean value for each variable. Column (6) shows the p-value for joint orthogonality.

Table A3: Summary Statistics and Balance Check for New Cohort

	Gain (1)	Loss (2)	SMS (3)	Control (4)	Overall (5)	Orthogonality† (6)
Father has at least primary education	0.430	0.400	0.480	0.424	0.434	0.715
Mother has at least primary education	0.390	0.460	0.480	0.556	0.471	0.132
Father has at least secondary education	0.070	0.100	0.140	0.121	0.108	0.380
Mother has at least secondary education	0.040	0.060	0.080	0.061	0.060	0.684
Household size	4.710	4.520	4.650	4.737	4.654	0.472
Male members in household	2.580	2.320	2.370	2.566	2.459	0.170
Female members in household	2.120	2.200	2.280	2.172	2.193	0.712
Owns residential land	0.990	0.980	0.990	0.980	0.985	0.878
Owns agricultural land	0.220	0.320	0.380	0.253	0.293	0.064
Has television or radio	0.350	0.430	0.500	0.535	0.454	0.040
Has a bicycle	0.550	0.520	0.490	0.596	0.539	0.483
Has a tube well	0.960	0.990	0.970	0.980	0.975	0.501
Has an electric fan	0.810	0.840	0.860	0.879	0.847	0.584
Weight of the child	41.340	40.010	41.630	41.717	41.173	0.249
Height of the child	58.490	58.980	57.540	57.495	58.128	0.198
Standardized test score	-0.192	-0.079	-0.250	0.000	-0.136	0.243
Observations	100	100	100	99	399	0.032

Note: There are 399 students from the new cohort since one student from the old cohort was mistakenly listed in the roster of new cohort, and was dropped upon realization. The first four rows are dummy variables that take a value of 1 if the male household head has at least primary and secondary education and the female household head has at least primary and secondary education, and 0 otherwise, respectively. Ownership of assets (agricultural land, radio/television, bicycle, tube well, electric fan) is a binary variable that takes a value of 1 if the household owns the asset, and 0 otherwise. The weight of the child is measured in kilograms, and the height of the child is measured in inches. Test scores are normalized relative to control mean and standard deviation. Column (5) shows the mean value for each variable. Column (6) shows the p-value for joint orthogonality.

Table A4: Does our Intervention Induce Students to Leave School Early?

Dependent variable	Afternoon attendance	
	(1)	(2)
Gain	0.053***	0.046***
	(0.012)	(0.011)
Loss	0.056***	0.050***
	(0.012)	(0.010)
SMS	0.025*	0.028**
	(0.013)	(0.011)
P(Gain = Loss)	0.766	0.649
P(Gain = SMS)	0.017	0.090
P(Loss = SMS)	0.008	0.030
Observations	73,423	73,423
R-squared	0.005	0.105
Control Mean	0.841	0.841
Cohort-School-Grade FE	No	Yes
Day FE	No	Yes
Control Variables	No	Yes

Note: The above observations are for valid school days in which the child was present in school according to the morning attendance record. "Afternoon attendance" takes a value of 1 if the child was present in school in the afternoon, and 0 otherwise. The Control treatment arm is the reference category in all regressions. The *p*-values for the test of equality of means between two different treatment arms are given in the middle panel. The control variables are ownership of agricultural land and radio/television. Standard errors clustered at the individual level are given in parentheses. ***, **, and * denote statistical significance at 1, 5, and 10 percent levels, respectively.

Table A5: Treatment Effect for All Students: Experimental Design

Dependent variable	Morning (1)	Afternoon (2)	Morning & Afternoon (3)	Random visit (4)
Gain	0.100***	0.115***	0.118***	0.085***
	(0.025)	(0.026)	(0.026)	(0.026)
	[0.000]	[0.000]	[0.000]	[0.001]
Loss	0.105***	0.123***	0.125***	0.121***
	(0.025)	(0.026)	(0.026)	(0.026)
	[0.000]	[0.000]	[0.000]	[0.000]
SMS	0.035	0.043*	0.044*	0.063**
	(0.025)	(0.025)	(0.025)	(0.026)
	[0.145]	[0.093]	[0.093]	[0.024]
P(Gain = Loss)	0.861	0.785	0.826	0.178
P(Gain = SMS)	0.017	0.011	0.008	0.394
P(Loss = SMS)	0.009	0.005	0.004	0.025
Observations	123,500	123,500	123,500	8,869
R-squared	0.008	0.011	0.011	0.009
Control mean	0.534	0.481	0.449	0.605

Note: “Morning" takes a value of 1 if the child was present in school in the morning, and 0 otherwise. “Afternoon" takes a value of 1 if the child was present in school in the afternoon, and 0 otherwise. “Morning and Afternoon" takes a value of 1 if the child was marked present in both the morning and afternoon attendance record, and 0 otherwise. “Random visit" takes a value of 1 if the child was present in school on the day of the random visit, and 0 otherwise. The Control treatment arm is the reference category in all regressions. The *p*-values for the test of equality of means between two different treatment arms are given in the middle panel. Standard errors clustered at the individual level are given in parentheses. The *p*-values for Westfall-Young correction for multiple hypothesis testing are given in square brackets below the standard errors. ***, **, and * denote statistical significance at 1, 5, and 10 percent levels, respectively.

Table A6: Treatment Effect for Continued Students: Baseline Specification

Dependent variable	Morning (1)	Afternoon (2)	Morning & Afternoon (3)	Random Visit (4)
Gain	0.117***	0.134***	0.136***	0.108***
	(0.022)	(0.024)	(0.024)	(0.026)
Loss	0.138***	0.157***	0.159***	0.146***
	(0.021)	(0.023)	(0.023)	(0.025)
SMS	0.060***	0.071***	0.071***	0.085***
	(0.022)	(0.023)	(0.023)	(0.026)
P(Gain = Loss)	0.379	0.342	0.377	0.133
P(Gain = SMS)	0.014	0.012	0.009	0.377
P(Loss = SMS)	0.001	0.000	0.000	0.015
Observations	110,800	110,800	110,800	8,460
R-squared	0.063	0.077	0.077	0.043
Control Mean	0.570	0.513	0.480	0.604

Note: Discontinued students are the ones who left the study at any point during the two year intervention period. There were 79 such students - 44 from the old cohort and 35 from the new cohort. This analysis drops such students. “Morning" takes a value of 1 if the child was present in school in the morning, and 0 otherwise. “Afternoon" takes a value of 1 if the child was present in school in the afternoon, and 0 otherwise. “Morning and Afternoon" takes a value of 1 if the child was marked present in both the morning and afternoon attendance record, and 0 otherwise. “Random visit" takes a value of 1 if the child was present in school on the day of the random visit, and 0 otherwise. The Control treatment arm is the reference category in all regressions. The p-values for the test of equality of means between two different treatment arms are given in the middle panel. The above specifications control for cohort-school-grade and day-fixed effects. They also control for unbalanced covariates at baseline - ownership of agricultural land and radio/television. Standard errors clustered at the individual level are given in parentheses. ***, **, and * denote statistical significance at 1, 5, and 10 percent levels, respectively.

Table A7: Does Discontinuity Matter?

Dependent variable	Discontinued		
	Old Cohort	New Cohort	Both cohorts
	(1)	(2)	(3)
Gain	-0.029	-0.030	-0.028
	(0.039)	(0.038)	(0.027)
Loss	0.005	-0.003	0.002
	(0.043)	(0.041)	(0.030)
SMS	-0.030	0.004	-0.013
	(0.042)	(0.041)	(0.030)
P(Gain = Loss)	0.427	0.479	0.285
P(Gain = SMS)	0.967	0.384	0.585
P(Loss = SMS)	0.428	0.861	0.624
Observations	400	399	799
R-squared	0.167	0.077	0.124
Control Mean	0.11	0.09	0.10

Note: Discontinued students are the ones who left the study at any point during the two year intervention period. There were 79 such students - 44 from the old cohort and 35 from the new cohort. "Discontinued" is a dummy variable if the individual left the study at any point in time, and 0 otherwise. The Control treatment arm is the reference category in all regressions. The *p*-values for the test of equality of means between two different treatment arms are given in the middle panel. The above specifications control for cohort-school-grade fixed effects. They also control for unbalanced covariates at baseline - ownership of agricultural land and radio/television. Standard errors clustered at the individual level are given in parentheses. ***, **, and * denote statistical significance at 1, 5, and 10 percent levels, respectively.

Table A8: Pre-intervention Analysis for New Cohort

Dependent variable	Days Attended		Attendance Rate	
	(1)	(2)	(3)	(4)
Gain	-0.365	-0.366	-0.019	-0.019
	(0.467)	(0.467)	(0.025)	(0.025)
Loss	0.285	0.285	0.014	0.014
	(0.485)	(0.486)	(0.026)	(0.026)
SMS	0.168	0.168	0.008	0.008
	(0.471)	(0.471)	(0.025)	(0.025)
P(Gain = Loss)	0.148	0.148	0.158	0.158
P(Gain = SMS)	0.216	0.216	0.243	0.243
P(Loss = SMS)	0.794	0.794	0.784	0.784
Observations	4,676	4,676	4,676	4,676
R-squared	0.041	0.299	0.036	0.112
Control Mean	10.595	10.595	0.556	0.556
Cohort-School-Grade FE	Yes	Yes	Yes	Yes
Month FE	No	Yes	No	Yes

Note: Daily attendance data is not available for non-intervention days. The outcome variables are derived from monthly attendance data for the year 2016 [2017] for the old [new] cohort. Grade 6 students in 2017 from the old cohort are dropped from the analysis since they went to a different primary institution in the preceding year, and we do not have their attendance data. “Days Attended" is the total number of days attended by a child in a given month. “Attendance Rate" for each student is calculated by dividing total number of days present in a month by total number of valid school days. The Control treatment arm is the reference category in all regressions. The *p*-values for the test of equality of means between two different treatment arms are given in the middle panel. They also control for unbalanced covariates at baseline - ownership of agricultural land and radio/television. Standard errors clustered at the individual level are given in parentheses. ***, **, and * denote statistical significance at 1, 5, and 10 percent levels, respectively.

Table A9: Treatment Effect: Clustering Errors at Different Levels

Dependent variable	Morning Attendance				
	(1)	(2)	(3)	(4)	(5)
Gain	0.107***	0.107*	0.107**	0.107*	0.104***
	(0.025)	(0.027)	(0.022)	(0.025)	(0.022)
Loss	0.112***	0.112**	0.112**	0.112***	0.102***
	(0.024)	(0.019)	(0.031)	(0.027)	(0.006)
SMS	0.048**	0.048	0.048**	0.048**	0.050**
	(0.024)	(0.020)	(0.014)	(0.021)	(0.018)
P(Gain = Loss)	0.859	0.648	0.667	0.796	0.937
P(Gain = SMS)	0.027	0.222	0.154	0.074	0.000
P(Loss = SMS)	0.014	0.129	0.213	0.051	0.024
Observations	123,500	123,500	123,500	123,500	107,750
R-squared	0.064	0.064	0.064	0.064	0.055
Control mean	0.534	0.534	0.534	0.534	0.534
Cluster Type	Individual	School	Grade	School-Grade	Section

Note: The number of observations when errors are clustered at the section level differs from other specifications since information on section was missing for 128 students. “Morning" takes a value of 1 if the child was present in school in the morning, and 0 otherwise. “Afternoon" takes a value of 1 if the child was present in school in the afternoon, and 0 otherwise. “Morning and Afternoon" takes a value of 1 if the child was marked present in both the morning and afternoon attendance record, and 0 otherwise. “Random visit" takes a value of 1 if the child was present in school on the day of the random visit, and 0 otherwise. The Control treatment arm is the reference category in all regressions. The p-values for the test of equality of means between two different treatment arms are given in the middle panel. The above specifications control for cohort-school-grade and day-fixed effects. They also control for unbalanced covariates at baseline - ownership of agricultural land and radio/television. Cluster type refers to the level at which standard errors are clustered. ***, **, and * denote statistical significance at 1, 5, and 10 percent levels, respectively.

Table A10: Treatment Effect by Phase

Dependent variable	Morning				Morning & Afternoon			
	2017-I	2017-II	2018-I	2018-II	2017-I	2017-II	2018-I	2018-II
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Gain	0.029	0.031	0.101***	0.208***	0.041	0.058	0.096***	0.240***
	(0.034)	(0.035)	(0.029)	(0.029)	(0.038)	(0.037)	(0.028)	(0.029)
Loss	0.030	0.039	0.091***	0.226***	0.055	0.057	0.091***	0.259***
	(0.031)	(0.033)	(0.029)	(0.030)	(0.035)	(0.035)	(0.029)	(0.028)
SMS	0.047	0.034	0.046	0.058**	0.066***	0.045	0.046	0.067**
	(0.033)	(0.034)	(0.030)	(0.028)	(0.037)	(0.036)	(0.029)	(0.026)
P(Gain = Loss)	0.969	0.823	0.733	0.556	0.720	0.984	0.881	0.550
P(Gain = SMS)	0.611	0.925	0.073	0.000	0.527	0.739	0.099	0.000
P(Loss = SMS)	0.613	0.897	0.152	0.000	0.760	0.749	0.141	0.000
Observations	24,000	19,600	39,950	39,950	24,000	19,600	39,950	39,950
R-squared	0.066	0.062	0.050	0.077	0.092	0.103	0.048	0.094
Control Mean	0.612	0.661	0.545	0.415	0.476	0.577	0.497	0.323

Note: Each of the columns indicates the point estimates for the different phases. The first four columns are for “Morning” attendance and the last four columns are for “Morning & Afternoon" attendance. “Morning" takes a value of 1 if the child was present in school in the morning, and 0 otherwise. “Morning and Afternoon" takes a value of 1 if the child was marked present in both the morning and afternoon attendance record, and 0 otherwise. The Control treatment arm is the reference category in all regressions. The *p*-values for the test of equality of means between two different treatment arms are given in the middle panel. The above specifications control for cohort-school-grade and day fixed effects. They also control for unbalanced covariates at baseline - ownership of agricultural land and radio/television. Standard errors clustered at the individual level are given in parentheses. ***, **, and * denote statistical significance at 1, 5, and 10 percent levels, respectively.

Table A11: Treatment Effect across Subtreatment Arms

Dependent variable	Morning (1)	Afternoon (2)	Morning & Afternoon (3)	Random Visit (4)
Gain High	0.218***	0.248***	0.249***	0.132***
	(0.037)	(0.037)	(0.037)	(0.047)
Gain Low	0.198***	0.224***	0.231***	0.133***
	(0.037)	(0.038)	(0.037)	(0.044)
Loss High	0.237***	0.266***	0.269***	0.211***
	(0.037)	(0.037)	(0.037)	(0.047)
Loss Low	0.216***	0.247***	0.249***	0.148***
	(0.038)	(0.037)	(0.036)	(0.045)
SMS	0.058**	0.069**	0.067**	0.078**
	(0.028)	(0.027)	(0.026)	(0.038)
P(Gain High = Gain Low)	0.657	0.598	0.698	0.973
P(Loss High = Loss Low)	0.648	0.660	0.643	0.220
P(Gain High = Loss High)	0.665	0.683	0.645	0.129
P(Gain Low = Loss Low)	0.685	0.619	0.697	0.770
Observations	39,950	39,950	39,950	2,463
R-squared	0.077	0.100	0.094	0.041
Control Mean	0.534	0.481	0.449	0.605

Note: The above results hold true only for phase 2 in 2018. “Morning" takes a value of 1 if the child was present in school in the morning, and 0 otherwise. “Afternoon" takes a value of 1 if the child was present in school in the afternoon, and 0 otherwise. “Morning and Afternoon" takes a value of 1 if the child was marked present in both the morning and afternoon attendance record, and 0 otherwise. “Random visit" takes a value of 1 if the child was present in school on the day of the random visit, and 0 otherwise. The Control treatment arm is the reference category in all regressions. The *p*-values for the test of equality of means between two different treatment arms are given in the middle panel. The above specifications control for cohort-school-grade and day fixed effects. They also control for unbalanced covariates at baseline - ownership of agricultural land and radio/television. Standard errors clustered at the individual level are given in parentheses. ***, **, and * denote statistical significance at 1, 5, and 10 percent levels, respectively.

Table A12: Impact Heterogeneity by Pre-intervention Attendance Rate

Dependent variable	Morning Attendance	
	Below median (1)	Above median (2)
Gain	0.071**	0.097***
	(0.032)	(0.030)
Loss	0.086***	0.084***
	(0.031)	(0.028)
SMS	-0.008	0.043
	(0.028)	(0.027)
$P(Gain_1 = Gain_2) = 0.549$		
$P(Loss_1 = Loss_2) = 0.965$		
$P(SMS_1 = SMS_2) = 0.178$		
Observations	46,340	46,125
Control Mean	0.534	0.695

Note: Column (1) shows the point estimates for students whose pre-intervention attendance was below median while Column (2) is for students whose pre-intervention attendance was above median. This analysis drops students who were in grade 6 in 2017 since they went to a different primary institution in the preceding year. “Morning Attendance" takes a value of 1 if the child was present in school in the morning, and 0 otherwise. The Control treatment arm is the reference category in all regressions. The *p*-values for the joint test of equality of the coefficients for the below-median and above-median students using seemingly unrelated regressions are given in the middle panel. The above specifications control for cohort-school-grade fixed effects only. They also control for unbalanced covariates at baseline - ownership of agricultural land and radio/television. Standard errors clustered at the individual level are given in parentheses. ***, **, and * denote statistical significance at 1, 5, and 10 percent levels, respectively.

Table A13: Impact Heterogeneity by Gender

Dependent variable	Morning Attendance	
	Male	Female
	(1)	(2)
Gain	0.082**	0.123***
	(0.035)	(0.035)
Loss	0.081**	0.136***
	(0.038)	(0.030)
SMS	0.003	0.074**
	(0.035)	(0.032)
$P(Gain_{male} = Gain_{female}) = 0.397$		
$P(Loss_{male} = Loss_{female}) = 0.247$		
$P(SMS_{male} = SMS_{female}) = 0.133$		
Observations	61,680	61,820
Control Mean	0.514	0.555

Note: Column (1) shows the point estimates for male students while Column (2) does the same for female students. "Morning Attendance" takes a value of 1 if the child was present in school in the morning, and 0 otherwise. The Control treatment arm is the reference category in all regressions. The *p*-values for the test of equality of the coefficients for male and female students using seemingly unrelated regressions are given in the middle panel. The above specifications control for the cohort-school-grade and day fixed effects. They also control for the unbalanced covariates at baseline - ownership of agricultural land and radio/television. Standard errors clustered at the individual level are given in parentheses. ***, **, and * denote statistical significance at 1, 5, and 10 percent levels, respectively.

Table A14: Impact Heterogeneity by Education Level of Parents

Dependent variable	Morning Attendance							
	Father has completed				Mother has completed			
	No education (1)	Primary education (2)	Secondary education (3)	Tertiary education (4)	No education (5)	Primary education (6)	Secondary education (7)	Tertiary education (8)
Gain	0.054	0.125**	0.143**	0.214***	0.049	0.144***	0.157***	0.148**
	(0.040)	(0.041)	(0.057)	(0.059)	(0.041)	(0.039)	(0.049)	(0.069)
Loss	0.084**	0.116**	0.179***	0.136**	0.088	0.161***	0.079	0.079
	(0.041)	(0.050)	(0.055)	(0.060)	(0.038)	(0.045)	(0.052)	(0.055)
SMS	0.071*	0.035	0.048	0.071	0.041	0.092**	0.039	0.010
	(0.040)	(0.053)	(0.056)	(0.066)	(0.039)	(0.043)	(0.051)	(0.069)
$P(Gain_{father,no} = Gain_{father,prim} = Gain_{father,sec} = Gain_{father,ter}) = 0.142$				$P(Gain_{mother,no} = Gain_{mother,prim} = Gain_{mother,sec} = Gain_{mother,ter}) = 0.248$				
$P(Loss_{father,no} = Loss_{father,prim} = Loss_{father,sec} = Loss_{father,ter}) = 0.567$				$P(Loss_{mother,no} = Loss_{mother,prim} = Loss_{mother,sec} = Loss_{mother,ter}) = 0.521$				
$P(SMS_{father,no} = SMS_{father,prim} = SMS_{father,sec} = SMS_{father,ter}) = 0.946$				$P(SMS_{mother,no} = SMS_{mother,prim} = SMS_{mother,sec} = SMS_{mother,ter}) = 0.710$				
Observations	46,365	33,155	17,940	10,585	49,500	34,310	24,465	6,275
Control Mean	0.517	0.547	0.566	0.565	0.532	0.516	0.576	0.615

Note: “Morning Attendance" takes a value of 1 if the child was present in school in the morning, and 0 otherwise. The Control treatment arm is the reference category in all regressions. The *p*-values for the joint test of equality of the coefficients for using seemingly unrelated regressions are given in the middle panel. The above specifications control for cohort-school-grade and day fixed effects. They also control for unbalanced covariates at baseline - ownership of agricultural land and radio/television. Standard errors clustered at the individual level are given in parentheses. ***, **, and * denote statistical significance at 1, 5, and 10 percent levels, respectively.

Table A15: Impact Heterogeneity by Distance from School

Dependent variable	Morning Attendance	
	Below median	Above median
	(1)	(2)
Gain	0.082**	0.127***
	(0.033)	(0.037)
Loss	0.088***	0.137***
	(0.032)	(0.035)
SMS	0.046	0.059*
	(0.036)	(0.033)
$P(Gain_1 = Gain_2) = 0.358$		
$P(Loss_1 = Loss_2) = 0.297$		
$P(SMS_1 = SMS_2) = 0.786$		
Observations	61,400	61,085
Control Mean	0.540	0.529

Note: Column (1) shows the point estimates for households whose distance to school is below the median distance while Column (2) is for households whose distance to school is above the median distance. “Morning Attendance" takes a value of 1 if the child was present in school in the morning, and 0 otherwise. The Control treatment arm is the reference category in all regressions. The *p*-values for the test of equality of the coefficients for above-median and below-median distance households using seemingly unrelated regressions are given in the middle panel. The above specifications control for the cohort-school-grade and day fixed effects. They also control for the unbalanced covariates at baseline - ownership of agricultural land and radio/television. Standard errors clustered at the individual level are given in parentheses. ***, **, and * denote statistical significance at 1, 5, and 10 percent levels, respectively.

Table A16: Impact Heterogeneity by Consumption Level

Dependent variable	Morning Attendance			
	1st Quartile (1)	2nd Quartile (2)	3rd Quartile (3)	4th Quartile (4)
Gain	0.069	0.120**	0.088*	0.150***
	(0.049)	(0.048)	(0.046)	(0.047)
Loss	0.087**	0.127***	0.130***	0.091**
	(0.047)	(0.047)	(0.045)	(0.045)
SMS	0.051	0.035	0.074	0.023
	(0.053)	(0.050)	(0.046)	(0.046)
$P(Gain_1 = Gain_2 = Gain_3 = Gain_4) = 0.647$				
$P(Loss_1 = Loss_2 = Loss_3 = Loss_4) = 0.868$				
$P(SMS_1 = SMS_2 = SMS_3 = SMS_4) = 0.879$				
Observations	24,980	26,270	27,495	29,005
Control Mean	0.491	0.517	0.590	0.533

Note: Each of the columns represents different consumption quartiles with quartile 1 comprising of households with the least consumption per capita and quartile 4 comprising of households with the highest consumption per capita. “Morning Attendance" takes a value of 1 if the child was present in school in the morning, and 0 otherwise. The Control treatment arm is the reference category in all regressions. The *p*-values for the joint test of equality of the coefficients for four consumption quartiles using seemingly unrelated regressions are given in the middle panel. The above specifications control for cohort-school-grade and day fixed effects. They also control for unbalanced covariates at baseline - ownership of agricultural land and radio/television. Standard errors clustered at the individual level are given in parentheses. ***, **, and * denote statistical significance at 1, 5, and 10 percent levels, respectively.

Table A17: Regression of CCT Recollection and Keeping SMS on Morning Attendance using Disbursement Surveys

Dependent variable	Morning Attendance Rate			
	(1)	(2)	(3)	(4)
Remembers CCT	0.182***	0.145***	0.145***	0.069***
	(0.022)	(0.024)	(0.024)	(0.023)
Kept SMS		0.062***	0.062***	0.021
		(0.022)	(0.022)	(0.018)
Loss			-0.001	
			(0.023)	
Observations	1,137	1,137	1,137	1,137
R-squared	0.083	0.090	0.090	0.775
Household FE	No	No	No	Yes
Phase FE	Yes	Yes	Yes	Yes

Note: The sample used in the above regressions is the set of households that belong to the gain and loss treatment groups. “Morning Attendance Rate" is the ratio of total number of days present in the morning over total valid number of school days in a given phase. “Remember CCT" takes a value of 1 if the interviewee (typically the head of the household) remembers the amount due, and 0 otherwise. “Kept SMS" takes a value of 1 if the records of the weekly SMS were found in the phone, and 0 otherwise. “Loss" is a dummy variable that takes a value of 1 if the child belongs to the Loss treatment group, and 0 otherwise. Households belonging to the Gain treatment arm form the reference category. All the specifications control for phase fixed effects. Standard errors clustered at the individual level are given in parentheses. ***, **, and * denote statistical significance at 1, 5, and 10 percent levels, respectively.

Table A18: Spillover across Sections

Dependent variable	Present Rate	
	(1)	(2)
Intervention Section X Month	0.033*	0.030
	(0.019)	(0.019)
Observations	13,234	13,234
R-squared	0.008	0.380
Grade FE	No	Yes
School FE	No	Yes
Month FE	No	Yes
Year FE	No	Yes

Note: The above table looks at section level aggregate attendance data for each year month combination. The dependent variable is “Present Rate" which is derived as the ratio of total number of days present to total valid school days in a given year and month. “Intervention Section X Month" is an interaction term that takes a value of 1 if there was at least one study participant in a given section and there were intervention days in that particular month, and 0 otherwise. Column (2) controls for grade, school, month, and year fixed effects with 2016 being the reference year for year fixed effects. Standard errors clustered at the section-year-month level are given in parentheses. Both the columns use total school days in a given month as frequency weights. ***, **, and * denote statistical significance at 1, 5, and 10 percent levels, respectively.

Table A19: Impact of Intervention on Post-intervention Enrollment Rate

Dependent variable	Full Sample	Male Enrollment Rate			Female Enrollment Rate		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Gain	0.032	0.059	-0.050	0.042	0.063	-0.048	0.157
	(0.045)	(0.099)	(0.104)	(0.115)	(0.094)	(0.121)	(0.134)
Loss	0.032	0.104	-0.095	-0.077	0.007	0.088	0.198
	(0.045)	(0.093)	(0.116)	(0.121)	(0.101)	(0.110)	(0.130)
SMS	0.072	0.140	-0.171	-0.061	0.092	0.214*	0.210*
	(0.044)	(0.091)	(0.109)	(0.123)	(0.094)	(0.111)	(0.121)
P(Gain = Loss)	1.000	0.617	0.699	0.310	0.545	0.245	0.736
P(Gain = SMS)	0.353	0.364	0.271	0.386	0.730	0.028	0.632
P(Loss = SMS)	0.353	0.666	0.529	0.895	0.356	0.236	0.908
Observations	799	155	143	102	163	141	93
Control Mean	0.704	0.725	0.750	0.792	0.737	0.579	0.652
R-squared	0.003	0.017	0.019	0.013	0.009	0.038	0.044
Grade in 2018	All	7	8	9	7	8	9

Note: The dependent variable is “enrolled in 2019". The first column looks at the impact of the intervention on the full sample in 2019. Columns (2)-(4) look at the impact on boys in 2019 and columns (5)-(7) do the same for girls. We use the grades of students in 2018 for the sub-sample analysis since information on grade is missing in 2019 for the non-enrolled students. The Control treatment arm is the reference category in all regressions. Standard errors clustered at the individual level are given in parentheses. ***, **, and * denote statistical significance at 1, 5, and 10 percent levels, respectively.

Table A20: Incidence of Child Marriage for Girls: Heterogeneity Analysis by Grade

Dependent variable	Female Child Marriage		
	(1)	(2)	(3)
Endline	0.083	0.105	0.261*
	(0.066)	(0.072)	(0.133)
Gain × Endline	-0.037	0.020	-0.166
	(0.081)	(0.110)	(0.162)
Loss × Endline	-0.083	-0.010	-0.311**
	(0.066)	(0.097)	(0.150)
SMS × Endline	-0.033	-0.105	-0.225
	(0.083)	(0.100)	(0.142)
Observations	316	282	184
R-squared	0.521	0.523	0.569
Grade in 2018	7	8	9

Note: The dependent variable is “Female Child Marriage".“Female Child Marriage" takes a value of 1 if the child is married, and 0 otherwise. There was one girl child from the new cohort who was separated at baseline and remained so at endline. We assumed her marriage status as “unmarried". The Control treatment arm is the reference category in all regressions. The above specifications control for household level fixed effects. Standard errors clustered at the individual level are given in parentheses. ***, **, and * denote statistical significance at 1, 5, and 10 percent levels, respectively.

Table A21: Impact of Intervention on Mathematics Test Score

Dependent variable	Endline score	
	(1)	(2)
Attendance Rate	-0.294	-0.484
	(0.814)	(0.782)
Baseline score	0.082**	0.079**
	(0.037)	(0.038)
Child is male		0.125
		(0.098)
Father has primary education		0.061
		(0.087)
Father has secondary education		0.102
		(0.159)
Mother has primary education		0.055
		(0.087)
Mother has secondary education		0.248
		(0.173)
Owns agricultural land		-0.090
		(0.083)
Owns radio or television		-0.159**
		(0.077)
Weight of child		0.001
		(0.006)
Height of child		-0.001
		(0.009)
Observations	718	718
Control Variables	No	Yes

Note: The mathematics test could be administered for 718 students at endline since the endline survey was conducted when schools were closed and the remaining 81 students were not at home when the research team visited the household to conduct the survey. Both baseline and endline test scores are normalized relative to control mean and standard deviation for every cohort-school-grade combination. The above estimates are obtained from instrumental variable regression where attendance rate is instrumented for by treatment assignment. The Control treatment arm is the reference category in all regressions. Column (1) regresses endline test score on baseline test score and treatment assignments. Column (2) adds household characteristics as control variables. Robust standard errors are given in parentheses. ***, **, and * denote statistical significance at 1, 5, and 10 percent levels, respectively.

Table A22: Classification of States by Minimum Legal Drinking Age in 2005-06

Banned	18	21	23	25
Gujarat	Jammu & Kashmir	Andhra Pradesh	Kerala	Delhi
Mizoram	Karnataka	Arunachal Pradesh		Haryana
Nagaland	Rajasthan	Assam		Maharashtra
	Sikkim	Bihar		Punjab
		Chhattisgarh		
		Goa		
		Himachal Pradesh		
		Jharkhand		
		Madhya Pradesh		
		Meghalaya		
		Orissa		
		Tamil Nadu		
		Tripura		
		Uttar Pradesh		
		Uttarakhand		
		West Bengal		

Note: The study includes households from all states in India except Manipur, where there was a partial lifting of alcohol ban in 2002 at the district level. Since DHS 2005-06 for India does not have information at the district level, we drop Manipur from our study.

Table A23: Prevalence of Violence: by Alcohol Ban

Type of Violence	Incidence of violence (in %)		p-value
	Banned	Allowed	
Less severe physical violence	**16.89**	**31.87**	**0.00**
Pushed, shook, or threw something	4.63	11.09	0.00
Slapped	15.32	31.09	0.00
Punched with fist or hit something harmful	2.40	8.79	0.00
Kicked or dragged	4.02	9.63	0.00
Twisted her arm or pulled her hair	5.11	12.88	0.00
Severe physical violence	**4.23**	**9.89**	**0.00**
Strangled or burnt	0.52	1.45	0.00
Threatened with knife/gun or other weapon	0.44	0.85	0.03
Sexual violence	**3.54**	**6.67**	**0.00**
Physically forced sex when not wanted	3.27	6.14	0.00
Forced other sexual acts when not wanted	1.00	3.03	0.00
Observations	2291	25520	

Note: The columns show the incidence of intimate partner violence across states that differ in availability of alcohol. An individual is defined to be a victim of intimate partner violence if she was subject to the above forms of violence by her spouse anytime in the past.

Table A24: Prevalence of Violence: by Minimum Legal Drinking Age

Type of Violence	Incidence of violence (in %)					p-value
	Banned	18	21	23	25	
Less severe physical violence	**16.89**	**21.18**	**36.21**	**16.81**	**25.47**	**0.00**
Pushed, shook, or threw something	4.63	7.02	13.04	6.55	7.46	0.00
Slapped	15.32	20.72	35.29	16.16	24.96	0.00
Punched with fist or hit something harmful	2.40	6.57	10.48	2.84	4.85	0.00
Kicked or dragged	4.02	6.54	11.37	3.28	6.18	0.00
Twisted her arm or pulled her hair	5.11	8.44	14.76	4.37	10.16	0.00
Severe physical violence	**4.23**	**6.77**	**11.71**	**3.28**	**6.26**	**0.00**
Strangled or burnt	0.52	1.53	1.63	1.31	0.74	0.00
Threatened with knife/gun or other weapon	0.44	1.13	0.95	0.66	0.32	0.00
Sexual violence	**3.54**	**6.34**	**7.82**	**5.02**	**2.93**	**0.00**
Physically forced sex when not wanted	3.27	6.00	7.13	4.59	2.78	0.00
Forced other sexual acts when not wanted	1.00	3.40	3.48	2.18	1.20	0.00
Observations	2,291	3,532	17,261	458	4,743	

Note: The columns show the incidence of intimate partner violence across states that differ in the minimum legal age for drinking. An individual is defined to be a victim of intimate partner violence if she was subject to the above forms of violence by her spouse anytime in the past.

Table A25: First Stage Results: Impact of Alcohol Ban on Alcohol Consumption

Dependent variable	Alcohol			
	(1)	(2)	(3)	(4)
Allowed	0.208***	0.229***	0.222***	0.220***
	(0.021)	(0.021)	(0.020)	(0.021)
Household members		-0.003	-0.005**	-0.003
		(0.002)	(0.002)	(0.002)
Rural household		-0.040***	-0.072***	-0.077***
		(0.012)	(0.012)	(0.012)
Age of female			-0.000	0.000
			(0.001)	(0.001)
Female has primary education			-0.037***	-0.016
			(0.012)	(0.013)
Female has secondary education			-0.086***	-0.034***
			(0.011)	(0.012)
Female has higher education			-0.172***	-0.053***
			(0.018)	(0.021)
Number of children			0.002	-0.000
			(0.003)	(0.003)
Female is pregnant			0.035**	0.032*
			(0.017)	(0.017)
Age of husband				-0.000
				(0.001)
Husband has primary education				-0.022*
				(0.013)
Husband has secondary education				-0.088***
				(0.012)
Husband has higher education				-0.197***
				(0.017)
Observations	28,285	28,285	28,285	28,285
R-squared	0.006	0.053	0.062	0.071
Control Mean	0.340	0.340	0.340	0.340
Household Controls	No	Yes	Yes	Yes
Respondent Controls	No	No	Yes	Yes
Husband Controls	No	No	No	Yes

Note: The dependent variable “alcohol " is a binary variable that takes a value of 1 if the husband consumes alcohol, and 0 otherwise. “Allowed" is a binary variable that takes a value of 1 if the individual is in a state where alcohol is allowed, and 0 otherwise. All of the above specifications adjust for weights from the domestic violence module. ‘Control Mean’ denotes mean alcohol consumption in states where alcohol is banned. Robust standard errors clustered at the primary sampling unit (PSU) level are given in parentheses. ***, **, and * denote statistical significance at 1, 5, and 10 percent levels, respectively.

Table A26: First Stage Results: Impact of Minimum Legal Drinking Age on Alcohol Consumption

Dependent variable	Alcohol			
	(1)	(2)	(3)	(4)
Above legal age	0.163***	0.175***	0.172***	0.175***
	(0.016)	(0.016)	(0.016)	(0.016)
Household members		-0.002	-0.004**	-0.003
		(0.002)	(0.002)	(0.002)
Rural household		-0.038***	-0.071***	-0.077***
		(0.009)	(0.009)	(0.009)
Age of female			-0.001	0.001
			(0.001)	(0.001)
Female has primary education			-0.037***	-0.016
			(0.012)	(0.012)
Female has secondary education			-0.089***	-0.036***
			(0.010)	(0.011)
Female has higher education			-0.176***	-0.057***
			(0.017)	(0.020)
Number of children			0.000	-0.002
			(0.003)	(0.003)
Female is pregnant			0.036**	0.031*
			(0.017)	(0.016)
Age of husband				-0.001
				(0.001)
Husband has primary education				-0.021*
				(0.012)
Husband has secondary education				-0.089***
				(0.012)
Husband has higher education				-0.198***
				(0.016)
Observations	28,285	28,285	28,285	28,285
R-squared	0.006	0.053	0.062	0.071
Control Mean	0.419	0.419	0.419	0.419
Household Controls	No	Yes	Yes	Yes
Respondent Controls	No	No	Yes	Yes
Husband Controls	No	No	No	Yes

Note: The dependent variable “alcohol consumption" is a binary variable that takes a value of 1 if the husband consumes alcohol, and 0 otherwise. Individuals in states where alcohol is banned or individuals who are below the legal drinking age in any state form the reference category. All of the above specifications adjust for weights from the domestic violence module. ‘Control Mean’ denotes mean alcohol consumption in states where alcohol is banned. Robust standard errors clustered at the primary sampling unit (PSU) level are given in parentheses. ***, **, and * denote statistical significance at 1, 5, and 10 percent levels, respectively.

Table A27: Impact of Alcohol Consumption on Intimate Partner Violence (all women)

Dependent variable	Less severe (1)	Severe (2)	Sexual (3)	Less severe (4)	Severe (5)	Sexual (6)
Alcohol	0.588***	0.265***	0.119***	0.524***	0.230***	0.0644
	(0.065)	(0.040)	(0.032)	(0.085)	(0.044)	(0.047)
Age of female	-0.001	-0.000	-0.001*	-0.002	-0.000	-0.000
	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)
Female has primary education	-0.014	0.002	-0.008*	-0.028**	-0.009	-0.020***
	(0.010)	(0.006)	(0.005)	(0.013)	(0.009)	(0.007)
Female has secondary education	-0.087***	-0.038***	-0.019***	-0.087***	-0.034***	-0.024***
	(0.009)	(0.005)	(0.004)	(0.013)	(0.008)	(0.007)
Female has higher education	-0.162***	-0.048***	-0.031***	-0.171***	-0.050***	-0.044***
	(0.015)	(0.009)	(0.008)	(0.020)	(0.010)	(0.009)
Number of children	0.034***	0.013***	0.006***	0.036***	0.016***	0.006***
	(0.002)	(0.001)	(0.001)	(0.003)	(0.002)	(0.002)
Female is pregnant	-0.003	-0.006	-0.003	-0.020	-0.013	-0.012
	(0.012)	(0.008)	(0.006)	(0.018)	(0.012)	(0.010)
Age of husband	-0.001*	-0.000	-0.000	-0.001	-0.001	-0.001*
	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)
Husband has primary education	0.017*	0.001	0.001	0.032**	0.006	0.002
	(0.010)	(0.006)	(0.005)	(0.013)	(0.009)	(0.007)
Husband has secondary education	-0.004	-0.014**	-0.005	0.010	-0.016*	-0.004
	(0.010)	(0.006)	(0.005)	(0.013)	(0.008)	(0.007)
Husband has higher education	-0.013	-0.012	0.007	0.015	-0.016	-0.000
	(0.017)	(0.010)	(0.008)	(0.020)	(0.010)	(0.009)
Observations	28,852	28,852	28,852	28,852	28,852	28,852
Weights	No	No	No	Yes	Yes	Yes
Control Mean	0.174	0.046	0.036	0.174	0.046	0.036

Note: The dependent variables are binary outcomes that take a value of 1 if the female experienced intimate partner violence anytime in the marriage, and 0 otherwise. “Alcohol" takes a value of 1 if the husband drinks alcohol, and 0 otherwise. All of the above specifications control for female, husband, and household characteristics. ‘Control Mean’ denotes mean intimate partner violence in states where alcohol is banned. Robust standard errors clustered at the primary sampling unit (PSU) level are given in parentheses. ***, **, and * denote statistical significance at 1, 5, and 10 percent levels, respectively.

Table A28: Impact of Alcohol Consumption on Physical Violence

Dependent variable	Pushed (1)	Slapped (2)	Twisted (3)	Punched (4)	Kicked (5)	Strangled (6)	Threatened (7)
Alcohol	0.250***	0.542***	0.340***	0.298***	0.225***	0.047***	0.030***
	(0.055)	(0.084)	(0.051)	(0.045)	(0.044)	(0.012)	(0.010)
Age of female	-0.000	-0.002	-0.000	0.000	-0.000	-0.000	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)
Female has primary education	-0.018*	-0.029**	-0.019*	-0.024***	-0.009	-0.005*	0.001
	(0.010)	(0.013)	(0.010)	(0.008)	(0.009)	(0.003)	(0.002)
Female has secondary education	-0.032***	-0.087***	-0.059***	-0.042***	-0.033***	-0.006**	-0.002
	(0.009)	(0.014)	(0.009)	(0.008)	(0.008)	(0.003)	(0.002)
Female has higher education	-0.052***	-0.173***	-0.082***	-0.055***	-0.050***	-0.005	-0.004
	(0.012)	(0.021)	(0.013)	(0.011)	(0.011)	(0.003)	(0.002)
Number of children	0.020***	0.036***	0.015***	0.015***	0.016***	0.001	-0.000
	(0.003)	(0.004)	(0.003)	(0.002)	(0.002)	(0.001)	(0.001)
Female is pregnant	-0.014	-0.024	-0.019	-0.021**	-0.015	-0.003	-0.004
	(0.012)	(0.018)	(0.013)	(0.011)	(0.011)	(0.004)	(0.003)
Age of husband	-0.001	-0.001	-0.001	-0.001	-0.001	-0.000	0.0001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)
Husband has primary education	-0.001	0.036**	0.009	-0.009	0.006	0.002	-0.001
	(0.010)	(0.015)	(0.011)	(0.010)	(0.010)	(0.004)	(0.003)
Husband has secondary education	-0.006	0.014	-0.011	-0.004	-0.013	-0.005	-0.004
	(0.011)	(0.015)	(0.012)	(0.010)	(0.010)	(0.004)	(0.002)
Husband has higher education	0.002	0.027	-0.003	0.018	-0.011	-0.003	-0.003
	(0.016)	(0.025)	(0.016)	(0.014)	(0.015)	(0.004)	(0.003)
Observations	28,285	28,285	28,285	28,285	28,285	28,285	28,285
Control Mean	0.106	0.298	0.123	0.083	0.092	0.014	0.008

Note: The dependent variables are binary outcomes that take a value of 1 if the female experienced intimate partner violence anytime in the marriage, and 0 otherwise. “Alcohol" takes a value of 1 if the husband drinks alcohol, and 0 otherwise. All of the above specifications control for female, husband, and household characteristics. ‘Control Mean’ denotes mean intimate partner violence in states where alcohol is banned. Robust standard errors clustered at the primary sampling unit (PSU) level are given in parentheses. ***, **, and * denote statistical significance at 1, 5, and 10 percent levels, respectively.

Table A29: Are Gender Attitudes of Women Worse in States where Alcohol is Allowed?

Dependent variable	Woman does not justify being beaten by husband when she					Does not justify beating
	Goes outside	Neglects children	Argues with husband	Refuses sex	Cooks bad	
	(1)	(2)	(3)	(4)	(5)	(6)
Alcohol is allowed	-0.043**	-0.041**	0.042**	0.025	0.027	0.003
	(0.021)	(0.024)	(0.025)	(0.019)	(0.022)	(0.026)
Age of female	0.003***	0.006***	0.002**	0.003***	0.002**	0.005***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Female has primary education	0.029**	-0.017	0.031**	0.032***	0.039***	0.006
	(0.013)	(0.013)	(0.013)	(0.010)	(0.012)	(0.014)
Female has secondary education	0.099***	0.046***	0.093***	0.073***	0.079***	0.080***
	(0.012)	(0.013)	(0.012)	(0.010)	(0.011)	(0.013)
Female has higher education	0.221***	0.188***	0.199***	0.132***	0.148***	0.228***
	(0.019)	(0.021)	(0.020)	(0.014)	(0.016)	(0.024)
Number of children	0.008**	0.008***	0.004	0.007***	0.006**	0.003
	(0.003)	(0.003)	(0.003)	(0.002)	(0.003)	(0.004)
Female is pregnant	0.041**	0.020	0.040**	0.030**	0.044***	0.049***
	(0.016)	(0.017)	(0.016)	(0.013)	(0.013)	(0.018)
Age of husband	-0.003***	-0.006***	-0.002*	-0.004***	-0.003***	-0.005***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Husband has primary education	0.023*	-0.017	0.006	0.011	0.010	-0.002
	(0.013)	(0.013)	(0.013)	(0.011)	(0.012)	(0.013)
Husband has secondary education	0.059***	0.008	0.032***	0.033***	0.032***	0.022*
	(0.013)	(0.013)	(0.012)	(0.010)	(0.011)	(0.013)
Husband has higher education	0.123***	0.093***	0.080***	0.047***	0.073***	0.121***
	(0.017)	(0.018)	(0.018)	(0.014)	(0.015)	(0.020)
Observations	28,115	28,108	27,951	27,591	28,043	27,227
R-squared	0.048	0.037	0.040	0.033	0.037	0.050
Control Mean	0.634	0.446	0.594	0.825	0.808	0.365

Note: The dependent variables are binary outcomes that take a value of 1 if beating is not justified, and 0 otherwise. “Alcohol allowed" takes a value of 1 if the individual is from a state where alcohol is allowed, and 0 otherwise. All of the above specifications control for female, husband, and household characteristics and adjust for weights from the domestic violence module.‘Control Mean’ denotes average gender attitudes of women in states where alcohol is banned. Robust standard errors clustered at the primary sampling unit (PSU) level are given in parentheses. ***, **, and * denote statistical significance at 1, 5, and 10 percent levels, respectively.

Table A30: Heterogeneity Analysis by Type of House Structure

Dependent variable	Less severe			Severe			Sexual		
	Poor	Moderate	Good	Poor	Moderate	Good	Poor	Moderate	Good
Alcohol	0.803***	-0.237	0.497***	0.436***	0.013	0.178***	0.086	0.204	0.052
	(0.189)	(0.652)	(0.096)	(0.098)	(0.428)	(0.052)	(0.127)	(0.311)	(0.050)
Age of female	-0.001	-0.000	-0.002	-0.002	-0.000	-0.000	-0.003*	-0.005*	0.001
	(0.003)	(0.004)	(0.001)	(0.002)	(0.003)	(0.001)	(0.001)	(0.003)	(0.001)
Female has primary education	-0.039	0.001	-0.028*	-0.018	-0.011	-0.006	-0.018	0.011	-0.026***
	(0.027)	(0.044)	(0.017)	(0.017)	(0.028)	(0.011)	(0.013)	(0.023)	(0.008)
Female has secondary education	-0.068**	-0.019	-0.096***	-0.042**	0.004	-0.034***	-0.024	0.036*	-0.031***
	(0.029)	(0.041)	(0.017)	(0.017)	(0.023)	(0.009)	(0.015)	(0.024)	(0.009)
Female has higher education	-0.237**	-0.102	-0.170***	-0.084	-0.039	-0.047***	-0.080***	-0.028	-0.053***
	(0.108)	(0.206)	(0.023)	(0.054)	(0.135)	(0.012)	(0.025)	(0.102)	(0.011)
Number of children	0.024***	0.029*	0.040***	0.012***	0.013	0.018***	0.005	0.031***	0.005**
	(0.007)	(0.015)	(0.005)	(0.005)	(0.009)	(0.003)	(0.004)	(0.009)	(0.002)
Female is pregnant	-0.009	0.182**	-0.056***	-0.030	0.032	-0.018	-0.014	0.005	-0.013
	(0.041)	(0.085)	(0.021)	(0.025)	(0.063)	(0.013)	(0.021)	(0.044)	(0.011)
Age of husband	0.001	-0.000	-0.002	0.001	0.000	-0.00120	0.000	0.003	-0.002***
	(0.002)	(0.004)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)
Husband has primary education	0.048*	-0.067	0.036*	0.025	-0.021	0.001	0.002	-0.001	0.006
	(0.026)	(0.052)	(0.019)	(0.019)	(0.034)	(0.013)	(0.015)	(0.026)	(0.010)
Husband has secondary education	0.049	-0.134	0.009	0.027	-0.041	-0.030**	-0.015	-0.002	0.005
	(0.034)	(0.106)	(0.018)	(0.020)	(0.074)	(0.013)	(0.018)	(0.052)	(0.011)
Husband has higher education	0.062	-0.231	0.014	0.044	-0.076	-0.033*	-0.024	-0.008	0.012
	(0.075)	(0.230)	(0.027)	(0.039)	(0.150)	(0.017)	(0.038)	(0.106)	(0.014)
Observations	6,524	2,284	19,477	6,524	2,284	19,477	6,524	2,284	19,477
Control Mean	0.161	0.180	0.171	0.033	0.058	0.044	0.032	0.029	0.041

Note: The dependent variables are binary outcomes that take a value of 1 if the female experienced intimate partner violence anytime in the marriage, and 0 otherwise. “Alcohol" takes a value of 1 if the husband drinks alcohol, and 0 otherwise. Houses that had no walls or were made of cane, mud or grass were considered to be of a poor quality; houses that were constructed of bamboo, plywood, unburnt bricks, and cardboard were of a moderate quality, and houses made of cement and burnt bricks were of a good quality. All of the above specifications control for female, husband, and household characteristics, and adjust for weights from the domestic violence module. ‘Control Mean’ denotes mean intimate partner violence in states where alcohol is banned. Robust standard errors clustered at the primary sampling unit (PSU) level are given in parentheses. ***, **, and * denote statistical significance at 1, 5, and 10 percent levels, respectively.

Table A31: Heterogeneity Analysis by Previous Exposure to Violence

Dependent variable	Less severe			Severe			Sexual		
	No	Yes	Unsure	No	Yes	Unsure	No	Yes	Unsure
Alcohol	0.414***	0.655	0.622**	0.142***	0.960**	-0.000	0.058	-0.0753	-0.126
	(0.086)	(0.492)	(0.309)	(0.046)	(0.442)	(0.216)	(0.046)	(0.307)	(0.263)
Age of female	-0.001	-0.003	0.007	-0.000	-0.002	-0.001	-0.000	0.002	-0.005
	(0.001)	(0.004)	(0.005)	(0.001)	(0.004)	(0.003)	(0.001)	(0.002)	(0.004)
Female has primary education	-0.035**	-0.023	-0.005	-0.013	0.011	0.008	-0.012*	-0.033*	-0.079***
	(0.015)	(0.034)	(0.049)	(0.009)	(0.036)	(0.028)	(0.007)	(0.019)	(0.024)
Female has secondary education	-0.084***	-0.049	-0.143***	-0.033***	-0.032	0.018	-0.011	-0.046**	-0.058*
	(0.014)	(0.037)	(0.053)	(0.008)	(0.035)	(0.034)	(0.007)	(0.020)	(0.034)
Female has higher education	-0.135***	-0.161**	-0.499***	-0.043***	-0.014	-0.118**	-0.025***	-0.099***	-0.086**
	(0.021)	(0.065)	(0.099)	(0.010)	(0.067)	(0.047)	(0.009)	(0.035)	(0.039)
Number of children	0.0364***	0.0429***	0.0103	0.0142***	0.0249***	0.0151*	0.00607***	0.0107*	0.00410
	(0.004)	(0.008)	(0.013)	(0.003)	(0.009)	(0.008)	(0.002)	(0.006)	(0.008)
Female is pregnant	-0.009	-0.063	0.016	-0.011	-0.031	-0.079**	-0.012	0.018	-0.043
	(0.020)	(0.050)	(0.067)	(0.011)	(0.053)	(0.032)	(0.011)	(0.029)	(0.039)
Age of husband	-0.001	-0.002	-0.003	-0.001	-0.002	0.001	-0.001*	-0.003*	0.002
	(0.001)	(0.003)	(0.005)	(0.001)	(0.003)	(0.003)	(0.001)	(0.002)	(0.003)
Husband has primary education	0.035**	0.015	0.056	0.015	-0.004	0.030	0.015*	-0.050**	0.026
	(0.016)	(0.034)	(0.051)	(0.010)	(0.037)	(0.033)	(0.009)	(0.021)	(0.030)
Husband has secondary education	0.019	-0.017	0.036	0.003	-0.020	-0.087**	0.005	-0.044*	0.016
	(0.017)	(0.040)	(0.059)	(0.011)	(0.041)	(0.035)	(0.009)	(0.026)	(0.040)
Husband has higher education	0.012	0.050	0.202*	-0.006	0.094	-0.0342	0.009	-0.020	-0.071
	(0.025)	(0.110)	(0.103)	(0.015)	(0.101)	(0.072)	(0.012)	(0.069)	(0.056)
Observations	21,384	5,041	1,830	21,384	5,041	1,830	21,384	5,041	1,830
Control Mean	0.137	0.497	0.224	0.033	0.118	0.077	0.024	0.095	0.126

Note: “No" indicates that the female was not exposed to domestic violence in the past. “Yes" indicates that the female was exposed to domestic violence in the past. “Unsure" indicates that the female was not sure about exposure to domestic violence in the past. The dependent variables are binary outcomes that take a value of 1 if the female experienced intimate partner violence anytime in the marriage, and 0 otherwise. “Alcohol" takes a value of 1 if the husband drinks alcohol, and 0 otherwise. All of the above specifications control for female, husband, and household characteristics, and adjust for weights from the domestic violence module. ‘Control Mean’ denotes mean intimate partner violence in states where alcohol is banned. Robust standard errors clustered at the primary sampling unit (PSU) level are given in parentheses. ***, **, and * denote statistical significance at 1, 5, and 10 percent levels, respectively.

Table A32: Heterogeneity Analysis by Disparity in Education Level

Dependent variable	Less severe			Severe			Sexual		
	Less	Equal	More	Less	Equal	More	Less	Equal	More
Alcohol	0.764***	0.389***	0.609***	0.282***	0.196***	0.331***	0.062	0.070	0.095
	(0.165)	(0.094)	(0.185)	(0.084)	(0.061)	(0.091)	(0.089)	(0.055)	(0.078)
Age of female	-0.000	-0.002	-0.005	-0.002	0.001	-0.002	-0.001	0.000	-0.001
	(0.002)	(0.002)	(0.003)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
Number of children	0.046***	0.040***	0.051***	0.025***	0.014***	0.035***	0.010***	0.006**	0.018**
	(0.005)	(0.005)	(0.012)	(0.004)	(0.003)	(0.008)	(0.003)	(0.003)	(0.007)
Female is pregnant	-0.001	-0.019	-0.124**	-0.003	-0.017	-0.040	-0.001	-0.005	-0.027
	(0.036)	(0.023)	(0.054)	(0.022)	(0.015)	(0.032)	(0.014)	(0.014)	(0.023)
Age of husband	-0.002	-0.000	-0.001	0.000	-0.002	-0.002	-0.001	-0.001	-0.002
	(0.002)	(0.001)	(0.003)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
Observations	10,193	15,002	3,060	10,193	15,002	3,060	10,193	15,002	3,060
Control Mean	0.189	0.159	0.164	0.056	0.035	0.042	0.043	0.033	0.023

Note: “Less" indicates that the education level of the female is less than her husband. “Equal" indicates that the education level of the female is same as her husband. “More" indicates that the education level of the female is more than her husband. The dependent variables are binary outcomes that take a value of 1 if the female experienced intimate partner violence anytime in the marriage, and 0 otherwise. “Alcohol" takes a value of 1 if the husband drinks alcohol, and 0 otherwise. All of the above specifications control for female, husband, and household characteristics, and adjust for weights from the domestic violence module. ‘Control Mean’ denotes mean intimate partner violence in states where alcohol is banned. Robust standard errors clustered at the primary sampling unit (PSU) level are given in parentheses. ***, **, and * denote statistical significance at 1, 5, and 10 percent levels, respectively.

Table A33: State wise Implementation of Mid Day Meal Program

State	Implementation	
	Month	Year
Andhra Pradesh	January	2003
Arunachal Pradesh	July	2004
Assam	January	2005
Bihar	January	2005
Chhattisgarh	April	2002
Dadra & Nagar Haveli	February	2002
Daman & Diu	June	2003
Haryana	August	2004
Himachal Pradesh	September	2004
Jammu & Kashmir	April	2005
Karnataka	July	2003
Madhya Pradesh	January	2004
Maharashtra	January	2003
Manipur	November	2004
Meghalaya	January	2003
Mizoram	February	2006
Orissa	September	2004
Punjab	September	2004
Rajasthan	July	2002
Sikkim	October	2002
Tripura	April	2003
Uttar Pradesh	September	2004
Uttaranchal	July	2003
West Bengal	March	2005

Source: Chakraborty and Jayaraman (2019)

Table A34: Does Exposure to Mid Day Meal Program Impact Parents' Confidence in Government Schools?

Dependent variable	Confidence in Government Schools
	(1)
Exposure any	-0.043***
	(0.015)
Education level of most educated male	0.000
	(0.002)
Education level of most educated female	0.001
	(0.001)
Number of children in household	0.013**
	(0.006)
Number of persons in household	-0.009***
	(0.003)
Log(income of household)	-0.001
	(0.008)
Observations	12,782
R-squared	0.067

Note: Here, we restrict analysis to the sub-sample where at least one child attends government or government-aided school and no child attends private school. "Exposure any" takes a value of 1 if at least one child in the household was exposed to the mid day meal program for at least a year, and 0 otherwise. We also control for education levels of the most educated male and most educated female in the household, and also religion and caste of household and state fixed effects. Standard errors clustered at the PSU level are given in parentheses. ***, **, and * denote statistical significance at 1, 5, and 10 percent levels, respectively.

Table A35: Impact of Mid Day Meal Program on Educational Expenditure: Household Fixed Effects Specification

Dependent variable	School Fees	Books, Uniform, and Others
	(1)	(2)
Exposure	-0.227***	-0.025
	(0.045)	(0.021)
Child is female	-0.174***	-0.072***
	(0.019)	(0.010)
Father's education	-0.018	-0.004
	(0.014)	(0.007)
Mother's education	0.020	0.016**
	(0.015)	(0.008)
Observations	31,102	35,223
R-squared	0.918	0.936

Note: The dependent variables are the logarithm of the amount of educational expenditures on each child in a given household. "Exposure" takes a value of 1 if the child was exposed to the mid day meal program for at least a year, and 0 otherwise. "Father's education" and "mother's education" are measured in terms of number of years of schooling. We also control for age, standard, and birth order fixed effects, dummy for child of household head and religion, caste, place of residence, number of members in household, number of children in household, logarithm of total education expenditures of household and household fixed effects. Standard errors clustered at the PSU level are given in parentheses. ***, **, and * denote statistical significance at 1, 5, and 10 percent levels, respectively.

Table A36: Impact of Mid Day Meal Program on Shares in Educational Expenditures at the Intensive Margin

Dependent variable	School Fees (1)	Books, Uniform, and Others (2)
One year exposure	-0.165***	0.013
	(0.028)	(0.013)
Two year exposure	-0.255***	0.001
	(0.038)	(0.017)
Three year exposure	-0.246***	0.040
	(0.058)	(0.026)
Child is female	-0.167***	-0.052***
	(0.013)	(0.006)
Father's education	0.007***	-0.003***
	(0.002)	(0.001)
Mother's education	0.016***	-0.001
	(0.002)	(0.001)
Log(Income) of household	0.102***	-0.003
	(0.011)	(0.005)
Observations	31,102	35,223
R-squared	0.712	0.793

Note: The dependent variables are the logarithm of the amount of educational expenditures on each child in a given household. "Exposure" takes a value of 1 if the child was exposed to the mid day meal program for at least a year, and 0 otherwise. "Father's education" and "mother's education" are measured in terms of number of years of schooling. We also control for age, standard, and birth order fixed effects, dummy for child of household head and religion, caste, place of residence, number of members in household, number of children in household, logarithm of total education expenditures of household and state fixed effects. Standard errors clustered at the PSU level are given in parentheses. ***, **, and * denote statistical significance at 1, 5, and 10 percent levels, respectively.

Table A37: Impact of Mid Day Meal Program on Educational Expenditure: Addressing Concerns Regarding Inter-state Migration

Dependent variable	School Fees (1)	Books, Uniform, and Others (2)
Exposure	-0.180***	0.012
	(0.027)	(0.013)
Child is female	-0.168***	0.052***
	(0.013)	(0.006)
Father's education	0.007***	-0.003***
	(0.002)	(0.001)
Mother's education	0.016***	-0.001
	(0.002)	(0.001)
Log(income of household)	0.102***	-0.003
	(0.012)	(0.005)
Observations	30,375	34,487
R-squared	0.709	0.794
State Fixed Effects	Yes	Yes

Note: The dependent variables are the logarithm of the amount of educational expenditures on each child in a given household. "Exposure" takes a value of 1 if the child was exposed to the mid day meal program for at least a year, and 0 otherwise. "Father's education" and "mother's education" are measured in terms of number of years of schooling. We also control for age, standard, and birth order fixed effects, dummy for child of household head and religion, caste, place of residence, number of members in household, number of children in household, logarithm of total education expenditures of household and state fixed effects. Standard errors clustered at the PSU level are given in parentheses. ***, **, and * denote statistical significance at 1, 5, and 10 percent levels, respectively.

Table A38: Impact of Mid Day Meal Program on Educational Expenditure: Clustering Standard Errors at State Level

Dependent variable	School Fees (1)	Books, Uniform, and Others (2)
Exposure	-0.177***	0.010
	(0.057)	(0.024)
Child is female	-0.167***	-0.053***
	(0.028)	(0.013)
Father's education	0.007**	-0.003***
	(0.003)	(0.001)
Mother's education	0.015***	-0.001
	(0.003)	(0.002)
Log(income of household)	0.102***	-0.003
	(0.012)	(0.006)
Observations	31,102	35,223
R-squared	0.712	0.793

Note: The dependent variables are the logarithm of the amount of educational expenditures on each child in a given household. "Exposure" takes a value of 1 if the child was exposed to the mid day meal program for at least a year, and 0 otherwise. "Father's education" and "mother's education" are measured in terms of number of years of schooling. We also control for age, standard, and birth order fixed effects, dummy for child of household head and religion, caste, place of residence, number of members in household, number of children in household, logarithm of total education expenditures of household and state fixed effects. Standard errors clustered at the state level are given in parentheses. ***, **, and * denote statistical significance at 1, 5, and 10 percent levels, respectively.

Table A39: Placebo Test: Comparing Children in Primary Grades to Higher Grades in Non-treated States

Dependent variable	School Fees	
	(1)	(2)
Treated	-0.209	0.025
	(0.148)	(0.143)
Child is female	-0.127***	-0.129***
	(0.028)	(0.027)
Father's education	-0.003	-0.001
	(0.005)	(0.005)
Mother's education	0.016***	0.015***
	(0.005)	(0.005)
Log(income of household)	0.147***	0.120***
	(0.029)	(0.027)
Observations	5,451	5,451
R-squared	0.707	0.718
State FE	No	Yes

Note: The dependent variables are the logarithm of the amount of educational expenditures on each child in a given household. The above analysis is valid for the sub-sample of states where the mid day meal program was never implemented or implemented in 2005 and children who did not get exposure to the mid day meal program. "Treated" takes a value of 1 if the child was in grades 1 to 5, and 0 otherwise. "Father's education" and "mother's education" are measured in terms of number of years of schooling. We also control for age, standard, and birth order fixed effects, dummy for child of household head and religion, caste, place of residence, number of members in household, number of children in household, logarithm of total education expenditures of household and state fixed effects. Standard errors clustered at the state level are given in parentheses. ***, **, and * denote statistical significance at 1, 5, and 10 percent levels, respectively.

Table A40: Likelihood of Attending Government and Private School by Consumption Level

Dependent variable	Government School				Private School			
	1st Quartile	2nd Quartile	3rd Quartile	4th Quartile	1st Quartile	2nd Quartile	3rd Quartile	4th Quartile
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Exposure	0.074***	0.105***	0.081***	0.044***	-0.047***	-0.068***	-0.049***	-0.002
	(0.009)	(0.011)	(0.012)	(0.012)	(0.009)	(0.011)	(0.011)	(0.013)
Child is female	0.036***	0.038***	0.063***	0.055***	-0.040***	-0.035***	-0.062***	-0.044***
	(0.007)	(0.009)	(0.009)	(0.009)	(0.006)	(0.008)	(0.009)	(0.010)
Father's education	-0.005***	-0.011***	-0.010***	-0.012***	0.010***	0.004***	0.009***	0.010***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)
Mother's education	-0.012	-0.009**	-0.012***	-0.015***	0.010***	0.006***	0.009***	0.011***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
	$P(Gov_1 = Gov_2 = Gov_3 = Gov_4) = 0.002$				$P(Pvt_1 = Pvt_2 = Pvt_3 = Pvt_4) = 0.001$			
Observations	9,864	9,688	9,358	8,216	9,864	9,688	9,358	8,216

Note: Each of the columns represents different consumption quartiles with quartile 1 comprising of households with the least consumption per capita and quartile 4 comprising of households with the highest consumption per capita. The dependent variables are dummy variables that take a value of 1 if the child attends the respective school type, and 0 otherwise. "Exposure" takes a value of 1 if the child was exposed to the mid day meal program for at least a year, and 0 otherwise. "Father's education" and "mother's education" are measured in terms of number of years of schooling. We also control for age, standard, and birth order fixed effects, dummy for child of household head and religion, caste, place of residence, number of members in household, number of children in household and state fixed effects. The *p*-values for the joint test of equality of the coefficients across different quartiles using seemingly unrelated regressions are given in the middle panel. Standard errors clustered at the PSU level are given in parentheses. ***, **, and * denote statistical significance at 1, 5, and 10 percent levels, respectively.

Table A41: Impact Heterogeneity by Place of Residence

Dependent variable	School Fees	
	Rural	Urban
	(1)	(2)
Exposure	-0.319***	-0.187***
	(0.020)	(0.024)
Child is female	-0.180***	-0.134***
	(0.017)	(0.019)
Father's education	0.010***	0.001
	(0.003)	(0.003)
Mother's education	0.020***	0.015***
	(0.003)	(0.003)
Log(income of household)	0.108***	0.090***
	(0.014)	(0.017)
$P(Sch_{rur} = Sch_{urb}) = 0.000$		
Observations	14,874	9,201

Note: Each of the columns represents the type of residence of the household (rural/urban). The dependent variables are the logarithm of the amount of educational expenditures on each child in a given household. "Exposure" takes a value of 1 if the child was exposed to the mid day meal program for at least a year, and 0 otherwise. "Father's education" and "mother's education" are measured in terms of number of years of schooling. We also control for age, standard, and birth order fixed effects, dummy for child of household head and religion, caste, number of members in household, number of children in household, logarithm of total education expenditures of household and state fixed effects. The *p*-values for the joint test of equality of the coefficients between the two sub-samples using seemingly unrelated regressions are given in the middle panel. Standard errors clustered at the PSU code level are given in parentheses. ***, **, and * denote statistical significance at 1, 5, and 10 percent levels, respectively.

Table A42: Likelihood of Attending Government and Private School by Place of Residence

Dependent variable	Government School		Private School	
	Rural	Urban	Rural	Urban
	(1)	(2)	(3)	(4)
Exposure	0.076***	0.070***	-0.049***	-0.023**
	(0.007)	(0.010)	(0.006)	(0.011)
Child is female	0.047***	0.051***	-0.046***	-0.054***
	(0.005)	(0.008)	(0.005)	(0.008)
Father's education	-0.009***	-0.013**	0.009***	0.001***
	(0.001)	(0.002)	(0.001)	(0.002)
Mother's education	-0.015***	-0.011***	0.012***	0.007***
	(0.001)	(0.002)	(0.001)	(0.002)
	$P(Rural_{gov} = Urban_{gov}) = 0.635$		$P(Rural_{pvt} = Urban_{pvt}) = 0.050$	
Observations	24,402	12,249	24,402	12,249

Note: Each of the columns represents the type of residence of the household (rural/urban). The dependent variables are dummy variables that take a value of 1 if the child resides in the particular place, and 0 otherwise. "Exposure" takes a value of 1 if the child was exposed to the mid day meal program for at least a year, and 0 otherwise. "Father's education" and "mother's education" are measured in terms of number of years of schooling. We also control for age, standard, and birth order fixed effects, dummy for child of household head and religion, caste, number of members in household, number of children in household and state fixed effects. The *p*-values for the joint test of equality of the coefficients between the two sub-samples using seemingly unrelated regressions are given in the middle panel. Standard errors clustered at the PSU code level are given in parentheses. ***, **, and * denote statistical significance at 1, 5, and 10 percent levels, respectively.