No Free Lunch: Using Technology to Improve the Efficacy of School Feeding Programs *

Sisir Debnath† Sheetal Sekhri ‡

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This is a preliminary draft.

Abstract

Malnutrition among vulnerable children is often targeted using free school feeding programs in developing countries. This paper studies the role of technology in improving the delivery of school feeding programs. Using the roll-out of a mobile based monitoring mechanism (Interactive Voice Response System or the IVRS) that aids in cross tallying the number of beneficiaries reported by multiple agents in the delivery chain, we find that increase in resulting accountability reduces leakages in school lunch provision in Bihar, India. We contrast provision of meals in districts of Bihar and its contiguous neighboring states from an independent survey with the official state records. Independently collected data reveals that the technology reform increases the likelihood of lunch provision in a school by 20 percentage points. These results are robust to a number of specifications. The increase in take-up is also accompanied by an improvement in the quality and quantity of meals. By contrast, using official state records, we find that likelihood of lunch provision by a school declined post-reform. Surprisingly, the amount of rice consumed and cooking costs per school within district increase. Using trend break specifications and the independently collected data, we find that the reform resulted in a decrease in reported enrollment in schools and a substantial increase in attendance. Taken together, we interpret our findings to provide evidence that the IVRS resulted in the reduction in leakage in the school feeding program.

Key Words: Welfare programs, Mid-day meals, ICT, Leakages
JEL Codes: D73, I38, O31, H53, H51

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†Indian School of Business, Email: sisir_debnath@isb.edu

‡University of Virginia, Email: ssekhri@virginia.edu

1 Introduction

Social welfare programs in developing countries are infamous for poor administration and "leakages" from the distribution networks. Large swathes of benefits do not reach the intended beneficiaries (World Bank, 2003). In many countries, institutional capacity to implement safety net programs successfully is diminutive to the point of being deemed "failing" (Pritchett, 2009). Development outcomes tied to the public institutions that deliver them are undermined as a result of this failing. There is little empirical evidence uncovering what can improve the efficacy of public service delivery and importantly, reduce leakages in the delivery system.

Leakages in welfare programs targeted towards health and education of children can have far-reaching consequences. Significant malnourishment among children results in adverse health and education outcomes.[1] Consequently, public investment in school feeding programs as levers to combat malnourishment can get undermined if there are widespread leakages in the program.

In this paper, we study one of the largest school feeding programs, the mid-day meal (MDM) in Bihar, India. We evaluate the impact of a state-driven technology enabled reform and make two contributions. First, we show that information and communication technologies (ICT) can be harnessed to improve transparency and accountability in the delivery systems. Second, we demonstrate that technology-enabled improvements in delivery system enhance the efficacy of the scheme leading to significant increase in the provision of meals to the beneficiaries. This is accompanied by a significant increase in school attendance.

Our paper uses the statewide roll-out of Interactive Voice Response System (IVRS) introduced by the state of Bihar in establishing how it impacts the functioning of the MDM program. Despite being one of the top three global producers of wheat, rice, and pulses, the incidence of malnutrition among children in India is very high. By one estimate, India accounts for 40 percent of malnourished children in the world (von Braun *et al.*, 2008). To combat malnutrition, the National Program of Nutritional Support to Primary Education (popularly known as the mid-day meal or MDM Scheme) was launched by the Indian government in 1995. The scheme entitles each enrolled child to a meal on the school premises each school day. The program currently benefits 120 million primary school children across the country making it one of the largest school feeding programs in the world (Ministry of Human Resource Development, India). However, this program is fraught with corruption and inefficiencies.[2] Improving the effectiveness of this program can potentially induce better nutrition and education outcomes for children.[3] A key challenge faced by the top tier administration is that they have to rely on the take-up estimates provided by the middle-level delivery machinery to determine the future

[1]See Glewwe and Miguel (2008) for a survey article documenting the evidence.

[2]See for example http://www.dnaindia.com/india/1866691/comment-lack-of-monitoring-corruption-plague-mid-day-meal-scheme

[3]Figlio and Winicki (2005) show that improving accountability in US schools leads to better nutritional outcomes. But this study does not address how best to improve accountability.

allocations and performance of the program. Such estimates are often non-verifiable and leave room for rigging the statistics, siphoning off from the system, and inaction or shirking by the middle tier monitors of the system. As a result, a first-order policy goal is to ascertain how to improve information flow from the grass root level to the top tier. To this end, in 2012 the state of Bihar sidelined take-up information provision by the middle tier of the delivery machinery and introduced a fully automated platform that calls the school teachers every day to record whether the school provided the meal.

There are two ways in which this system can curtail leakages and improve the efficacy of the delivery system. First, the IVRS provides a way to cross tally information provided by the middle tier of the distribution system. Second, since beneficiary take-up information is available at much disaggregated level under the new system, it is possible to identify the schools that are not providing meals consistently. The middle tier bureaucrats are then held accountable for the performance of the school thereby inducing them to increase their effort to implement the MDM effectively.

We use state government reports for MDM and independent assessments of MDM by the central government and an independent NGO that monitors schooling outcomes in India every year to analyze the impact of this policy reform. We utilize the introduction of the program in 2012 in Bihar and compare the outcomes in districts of Bihar to comparable districts in its neighboring states before and after the introduction of the program.

In an independent assessment of the program where we employ the Annual Status of Education Report (ASER) data collected by Pratham, a national NGO, we find significant improvement in delivery. ASER team visits 30–40 schools in a district randomly every year and assesses a few schooling outcomes. Using this data, we find improvements in the percentage of schools providing MDM and the likelihood of whether MDM was cooked on the day of surprise visit. Our DID estimates echo these event study results and show that the percentage of schools providing MDM increased by 20 percentage points and the likelihood that MDM was cooked by 22 percentage points all significant at conventional levels of significance. These results are robust to a number of other specifications including controls for school characteristics, district specific trends, and a generalized DID where we match districts based on observables before implementing the DID estimates. Using trend break models with this same data, we find that enrollment in schools declined, whereas reported attendance increased.

We find evidence of malfeasance in reporting. As per State official data, a 100 percent of primary and upper primary schools in Bihar provided the school meals before the IVRS. However, after the program, we detect a statistically significant decline in the reported fraction of schools serving MDM. Our Bihar-based event study evidence is mirrored in our Difference-in-Difference estimates, where we find a reduction in the fraction of schools serving meals of a similar magnitude. Moreover, we find among the enrolled students, the percentage of those availing meals as per the official data declined by 34 and 37 percent for primary and upper primary schools in Bihar post the IVRS reform.

Although government estimates show a decline in the number of children availing meals, surprisingly, the amount of rice consumed and cooking cost which includes the cost of other materials added to meals increased. Finally, we examine the effects on quality of meals using an independent assessment conducted by the monitoring institutes recruited by the central government. We find that the likelihood of serving good quality meals at schools went up dramatically. Our DID estimates also suggest that provision of sufficient quantity of meals went up in Bihar after the reform.

Our paper extends three strands of literature. The first strand has focused on establishing low-cost monitoring or other mechanisms to improve the provision of public service delivery. Technology based monitoring by beneficiaries coupled with non-linear incentives has been demonstrated in inducing agents to exert effort (Duflo *et al.*, 2012), but this mechanism may not work so well where agents can also be co-opted to steal from the system. Encouraging communities to hold service providers more accountable may improve accountability in public service provision (Björkman and Svensson, 2009). Informal networks may facilitate monitoring and enforcement (Nagavarapu and Sekhri, 2015). But when large swathes of data and information are required to facilitate such empowerment, ICT technologies can reduce costs and be useful. We show that ICT technologies can also reduce the level of bureaucratic involvement in information flows within the systems, and thus reduce possibilities of malfeasance and shirking. Another notable contribution of our paper is to isolate a technology-based policy change that can increase state capacity in delivering services. Using an experiment, Muralidharan *et al.* (2014) show that payment infrastructures can be improved using biometric payment cards. Our paper complements such new evidence and shows that technology can be used to design simple mechanisms that can increase state capacity to monitor agents in welfare delivery programs so that agency problems can be reduced.

Our paper also extends the burgeoning literature examining the effects of ICT-enabled platforms on development outcomes. ICT enabled technologies have been demonstrated to improve producer surplus and reduce price dispersion in markets in India (Jensen, 2007; Goyal, 2010). Mobile phones have been linked to increasing access to credit, financial services, information, and have served as reminders in health care provision.[4] However, the role of ICT technologies in improving transparency and public service delivery is not well established. Our study addresses this gap.

Finally, our study complements and extends the literature on school feeding programs in developing countries. Jacoby (2002) examines the impact of the availability of school-based food programs on feeding behavior of parents at home using Philippines data. The study found that parents do not reduce food given to children at home in response to the availability of a school feeding program. Vermeersch and Kremer (2005) estimate the impact of a preschool feeding program in 50 Kenyan preschools finding significant improvements in participation rates and cognition test scores. Afridi *et al.* (2013) study the extension of the MDM in Delhi India to

[4] Aker and Mbiti (2010) provide an excellent overview.

upper primary schools and conclude that it leads to improved classroom effort among seventh graders. Our study extends this vein of work and shows that technology can be harnessed to improve the implementation of the school feeding programs thereby increasing school attendance.

Rest of the paper is organized as follows: Section 2 provides a background highlighting the features of the MDM program and the IVRS reform in Bihar. Section 3 discusses our data sources. In section 4, we provide a discussion of our estimation strategy. Section 6 discusses the results, and Section 7 concludes.

2 Background

2.1 MDM Program and Subsidies

The National Program of Nutritional Support to Primary Education, commonly known as the mid-day meal program, was introduced in selected parts of India in 1995.[5] This program entitled each student in public primary schools a free lunch. Initially, the program provided 100 grams of take-home grains every day, but in 2004, it transitioned from raw grains to cooked meals. Each of these meals was supposed to provide 300 calories of energy and 8-12 grams of protein. These requirements were revised in 2006 again and stipulated 450 calories and 12 grams of protein per meal with a particular focus to provide iron, folic acid, and other essential micronutrients. The 2006 revision also doubled the subsidy for cooking and preparation of meals.[6] Currently, the program covers all primary and upper primary Government and Government aided schools including *Madarsas* and *Maqtabs*.

The cost components of the program can be broadly classified as recurring and non-recurring. Recurring costs include expenditures on food grains, cooking ingredients, wages to cooks and helpers, and monitoring. Non-recurring costs cover infrastructure costs, such as building kitchen sheds and utensils. Assistance from the central government cover all non-recurring costs, foodgrains, and monitoring costs, while the rest of the cost is shared between the center and the states in a 75:25 ratio.[7] Most of the recurring grants are based on school level consumption and, therefore, vary by school. Schools estimate and report their annual requirement based on the number of students consuming meals and the number of expected working days. This information is aggregated at the block, district, and state levels. Based on these aggregated reports, state governments prepare an Annual Work Plan and Budget (AWP&B) and submit them to the Project Approval Board (PAB) of the Ministry of Human Resource Development

[5] Initially, the program was restricted to 2,408 blocks but was extended nationwide in 1997.

[6] Subsidy for cooking costs were increased from Rs. 1 to Rs. 2 per meal. For the North Eastern states the central government provided 90% of the subsidies while it was limited to 75%, for the rest of India. The state governments contributed the residual amounts.

[7] States that were unable to finance the costs were initially allowed to distribute raw grain. However, a Supreme Court judgment in 2001 mandated all public schools to provide cooked meals. Bihar started providing cooked meals in all primary schools in 2005.

(MHRD) for review and approval. PAB approvals determine actual allocations and the release of funds.

2.2 Monitoring and Allocation Disbursal

There are multiple monitoring mechanisms for the midday meal program. The institutional mechanism for monitoring rests with a four tier Steering-cum-Monitoring Committee at the national, state, district, and block level. The primary responsibility of these committees is to ensure that foodgrains and funds for cooking reach schools on time and meals are served as per norms. School Management Committees, comprising of parents and elected local leaders, are responsible for monitoring provision at a school level. Besides, the Government of India has also empaneled several Monitoring Institutes that are responsible for assessing the progress and quality of the MDM program in the districts. These institutes are required to cover five percent of total schools serving meals over a period of two years. Other than the institutional monitoring mechanisms monthly and quarterly progress reports submitted by the states to the central government are also used to assess performance.

Despite having a sound institutional framework, a recent study by Aiyar *et al.* (2013) finds local level monitoring as weak at best. The Block Resource Person (BRP) in Bihar, a contractual government employee, responsible for inspecting at least 30 schools every month, barely meets the target due to work overload. Other inspectors, such as the Cluster Resource Centre Coordinator (CRCC) often prefer to make phone calls to the headmaster rather than physically visit the schools. Delays in the disbursement of travel allowances, absence of feedback on the reports submitted by the inspectors, and lack of information on grievance redressal system often render monitoring toothless.

Grain and funds allocation for a school are determined by monthly requisitions submitted by the school headmaster to the Block Resource Person (BRP). These requests report the number of beneficiaries and the status of funds and food grains in a school. These requisitions are aggregated at the district level by the District offices. The process of a request for funds and crediting the amount to the school's account takes somewhere between two to three months. There is also a significant scope of siphoning both funds and food grains from this system. It is standard practice for schools to receive anywhere between five and eight kilos less for every 50 kg bag of grains (Aiyar *et al.*, 2013). The inadequate storage facility at schools force them to store grains in the local leaders or officials' residence. Schools collect stock from the storage facility on a need-to-take basis, and no formal records of withdrawals are maintained. Lack of weighing scales at local godowns and schools make it difficult to identify the source of leakage. Data provided by the intermediary officials on the number of requisitions submitted and processed, student attendance, number of beneficiaries, number of meals served, and infrastructure provided are routinely inflated as there are no means to verify the official records.

2.3 Interactive Voice Response System

The Bihar state mid-day meal authority streamlined the requisitions and allocations by making use of a Management Information System (MIS) for the requisition and transfer of funds and food grains. The middle tier employees of the department were still the main conduit of beneficiary take-up data to the top level administration. Thus to better assess and monitor school level provision of meals on real time basis, Bihar MDM authority implemented *Dopahar*, an Interactive Voice Response System (IVRS) that collected real-time data directly from the school teachers.

IVRS is a simple technology enabled mechanism that helps to cross tally the foodgrain and fund requests received by the BRPs. Under the IVRS, each school had to register 5 points of contact (cellular numbers) including one headmaster, two teachers, and two para-teachers. The IVRS calls any one of the five teachers in each school at random and collects data on the numbers of meals served at each school every day. If a school failed to serve any meals, the teacher is supposed to press 0 and provide the reason for the same. All the responses are categorical and pre-coded for the ease of data collection through mobile phones. In 2012, there were close to 70,000 schools in Bihar that were supposed to serve meals to students. Table A.1 shows the mobile penetration of the headmasters collected from the 'Dopahar' records. Over 99 percent of the headmasters had a cell phone and were contacted every day. After completing the calls to all of the schools, the IVRS system summarizes the data and generates reports at the district, block, village, and school level on attributes such as the number of attendees; meals served, adherence to menu, etc. The district level reports are e-mailed and texted to the District Magistrate, while the block level reports are sent to the Block Education Officer (BEO).

3 Model

The State MDM department delegates the task of serving lunch as schools to district and sub-district level administrative staffs and school teachers with very little oversight. This hierarchical setting resembles a standard principle-agent problem in the theory firms. In this section we develop a principle-agent model with and explore the comparative static effects of a decrease in monitoring cost on the agent's effort level.

As in a standard principle-agent model final output π depends on the agent's effort level e which unobserved by the principle. The principle is also unable to deduce the agent's effort level by observing the final output as π is stochastic. In a *good* state the final output is π_2, with probability $x(e)$, and in a *bad* state it is given by π_1. Agent's wage is given by w and his cost of exerting effort $\phi(e)$ is increasing in e. The cost of monitoring cost to the principle is c. It is only in the *bad* state the principle decides to inspect the agent's action and the probability of detection is given by d. Given the assumptions principles payoff is given by

$$\pi = x(e)(\pi_2 - w) + (1 - x(e))(1 - d)(\pi_1 - w) + (1 - x(e))d(\pi_1 - w - c).$$

$$\pi = x(e)(\pi_2 - \pi_1 + cd) + \pi_1 - w(e) - cd. \tag{1}$$

3.1 Agent's Problem

If the principle desires the agent to exert e^* effort it must be compatible with the agent's incentives. The *incentive compatibility* condition, $w(e^*) - \phi(e^*) \geq w(e^*)[x(e) + (1 - x(e))(1 - d)] - \phi(e)$, simplifies as

$$\phi(e^*) - \phi(e) \leq w(e^*)d(1 - x(e)). \tag{2}$$

If the principal can choose e^* such that agent's incentive compatibility is satisfied at $e = e_0$, where

$$e_0 = arg\max_e \; w(e^*)(x(e) + (1 - x(e))(1 - d)) - \phi(e) \tag{3}$$

then e^* becomes incentive compatible for all e. Given the agent's reservation wage $\overline{w}$, his participation constraint is given by $w(e*) - \phi(e^*) \geq \overline{w}$. Further, if we assume $\overline{w} < w(e^*)(x(e_0) + (1 - x(e_0))(1 - d)) - \phi(e_0)$ then provided $\overline{w}$ is *incentive compatible*, *participation constraint* is trivially satisfied.

Solving (3) we obtain agent's optimal condition as $x'(e_0)w(e^*)d = \phi'(e_0)$. Solving the differential equation and assuming that for zero effort, $e = 0$, the agent's costs and the probability of a *good* state are at zero, we obtain

$$x(e_0)w(e^*)d = \phi(e_0). \tag{4}$$

Substituting the optimal condition for e^* in equation (2), the *incentive compatibility* condition at e_0 effort level, simplifies as

$$\phi(e^*) \leq w(e^*)d. \tag{5}$$

3.2 Principal's Problem

The principal's problem is to maximize his profit(1) given the agent's *incentive compatibility* in (5).

$$\begin{aligned} \max_{e^*, d} \quad & x(e^*)(\pi_2 - \pi_1 + cd) + \pi_1 - w(e^*) - cd \\ \text{subject to:} \quad & \phi(e^*) \leq w(e^*)d. \end{aligned}$$

Assuming interior solution for the probability of detection d, profit maximization requires the *incentive compatibility* condition to bind. This provides us the relationship between the probability of detection (d) and effort choice by the agent (e^*) as

$$\frac{\partial d}{\partial e^*} = \frac{\phi'(x^*)}{\phi(x^*)} - \frac{w'(x^*)}{w(x^*)} \tag{6}$$

Therefore, the optimal effort e^* increases with the chances of detection provided Assumption (1) is satisfied.

Assumption 1. *Cost elasticity of effort is larger than wage elasticity of effort at the optimal effort e^*.*

This assumption implies that the wage function is more concave than the cost function so that $\phi(e)/w(e)$ increases with e.

The other first order condition with respect to e^* can be written as

$$(\pi_2 - \pi_1 + cd) = \frac{w'(e^*)}{x'(e^*)} \tag{7}$$

3.3 Comparative Statics

The main objective of the model is to explore the effects of increase in the cost of monitoring. First let's consider the situation where the probability of detection increases with cost of monitoring. This implies that in order to maintain equation (7), $w'(e*)/x'(e*)$ has to increase. If the wage function ($w(e^*)$) is more concave than the probability function ($x(e^*)$) then the possibility of increase in d with increasing cost of monitoring is ruled out.

Alternatively, in response to an increase in c, d may decrease less than proportionately, causing the RHS of equation (7) to increase. Following a drop in the probability of detection d effort levels will decline. Given our assumption of the wage function is more concave than the probability function the RHS of the equation will increase in response to a decrease in e.

Assumption 2. *Wage function is more concave than the probability function, therefore, as c rises, d falls and effort e^* falls.*

Assumption 2 means that as the optimal effort increases, wage increases at a lower rate than the probability of *good* state. Since the only way increased effort affects the Principal's profit positively is through increasing the probability of *good* state, a necessary condition for the profit maximization to hold is if $w'(e^*)/x'(e^*)$ falls as e^* rises.

4 Data

We use three primary sources of data for carrying out our analysis. The independent assessment is based on the Annual Status of Education Reports (ASER) carried out by an NGO *Pratham*. ASER primarily covers educational achievement of primary and upper primary school children in every rural district in India. Each year the survey roughly covers 570 districts, 15,000 villages, 15,000 government schools, 300,000 households and 700,000 children between 5-16. We use ASER survey data to estimate the effects of the IVRS on the provision of mid-day meals at school. These surveys are available from 2005 onward, but the survey instruments are uniform, and the variables of interest are readily comparable for the period 2009–2014. Therefore, we restrict our estimation sample to this period. Furthermore, we restrict our analysis to five states in India which are similar to the state of Bihar in terms of many socio-economic aspects and geographical proximity. Our sample includes Bihar, Chhattisgarh, Jharkhand, Orissa, and Madhya Pradesh.[8] The estimation sample is a representative repeated cross section at the school and household level.

For each village surveyed under ASER, one government school (if any) is inspected randomly. For each of the inspected schools between 2009-2014, ASER collected information on two vital variables: whether meals were served in a school on the date of interview and whether the interviewer found any evidence of meals being cooked in the school. Other than these observations on MDM, ASER also collects information on physical school infrastructures such as the source of drinking water, provision of toilets, whether the school has a boundary wall and questions regarding teaching staff such as the number of teachers appointed and the number of teacher present on the day of the interview. The sample includes 6,392 schools in Bihar and 25,329 schools for the entire sample of five states.

The household module of the ASER surveys evaluate arithmetic and reading comprehension (in their native language) of all children between 3-16 age group. The arithmetic tests gauge the aptitude of children whether they can recognize numbers between 1-9, recognize numbers between 10-99, perform subtraction, and division. These categories are mutually exclusive and exhaustive. We use this information to create a categorical variable taking values from 0 to 4 that capture arithmetic learning. A score of zero implies that a child is unable to recognize numbers, a score of one means that the child can understand numbers between 1-9, for children knowing numbers between 10-99 a score of two is awarded, subtraction and division skills are rated as three and four, respectively. Similarly, the five categories for reading comprehension questions are whether the child is unable to read anything, read letters, words, read a paragraph, and finally, read a story.

Our second dataset comes from government records. We use district level Annual Work Plan Budgets (AWPB) that are submitted by the state mid-day meal authorities to the Government of India for review of their performance and approval of their budget for the period 2009-13. Each state has a district wise annual target of the meals that they want to serve. In addition to these goals, these reports include the total number of schools in existence, number of schools serving mid-day meals, total enrollment, children availing meals, the amount of rice

[8]Uttar Pradesh is also comparable and is an immediate neighbor. We do not include Uttar Pradesh in our sample as it introduced IVRS in 2010. However, we do not have access to the government records for the state. As a result, we are not able to include it in our sample.

consumed, and cooking costs. These data are available for both primary and upper primary schools at the district level. Our Bihar data has 38 districts and 228 district-year observations. Our event study analysis is based on this sample. Overall, there are 157 districts and 958 district-year observations in our sample of five states.

To explore the quantity and quality of meals we use audit reports published by independent monitoring institutes.[9] These institutes are appointed by the central government to audit state MDM programs. Each district is assigned to one of the empaneled monitoring institutes and within a period of two years, they inspect 5 percent of the elementary schools. Post monitoring the institutes submit half-yearly reports to the authorities. Apart from examining the daily operations of schools, these reports assess the quality and quantity of mid-day meals on the day of their visit. These assessments are qualitative, and the reports publish the number of schools where the quality and quantity of the meals are found to be good, satisfactory, or bad. We use these reports to create a district-wise panel of inspected schools that serve good and bad quality meals, and sufficient and insufficient quantity meals.[10] We have 180 district-year observations in this sample.

5 Estimation

In order to assess the effect of the IVRS on provision of mid-day meals, we estimate three types of empirical models. First, we use an event study framework to investigate the effects of the program on outcomes related to mid-day meal provision in Bihar before and after the introduction of the IVRS examining how the outcomes trend over years and whether changes in outcomes occur precisely after the policy change. The empirical model is specified as:

$$y_{dt} = \alpha_0 + \sum_{-3 \leq k \leq 2} \alpha_k \times \text{IVRS operational for } k \text{ periods} + \alpha_X X_{dt} + \delta_d + \varepsilon_{dt}, \tag{8}$$

where y_{dt} is an outcome variable measuring provision of meals in district d in year t. IVRS operational for k periods is an indicator variable equal to one if IVRS is in effect since k years and zero otherwise. A negative value of k implies it is a pre-IVRS period. X_{dt} is a vector of schools characteristics at the district level.[11] The specification also includes district fixed effects (δ_d). We estimate equation 8 after restricting data to the state of Bihar. The parameters of interest are α_ks.

Second, in order to allay the concern that secular trends over time may be responsible for

[9] Most of these institutes are headed by tenured professors at state universities.

[10] These reports are available at http://mdm.nic.in/#. It is possible that these data are not accurate due to co-opting of the monitors. However, these data were used to flag non-compliance and quality issues to Bihar government in 2010 preceding an accident where due to poor storage, school food rations got mixed with chemical fertilizers and caused the death of several students who consumed the food.

[11] School level characteristics include fraction of schools with separate girls toilet, drinking water, playground; number of head teachers, total appointed teachers.

the changes that we are attributing to the IVRS, we estimate a difference-in-difference model. We compare the effects of the IVRS on meals provision across the districts of Bihar and control states before and after the policy change.[12] The empirical model is as follows:

$$y_{dt} = \beta_0 + \sum_{-3 \leq k \leq 2} \beta_k \times \text{Bihar} \times \text{IVRS operational for } k \text{ periods} + \beta_X X_{dt} + \tau_t + \delta_d + \varepsilon_{dt}, \quad (9)$$

While other control variables remain the same as in the event study, here we interact the indicator for IVRS operational for k years with an indicator for treatment which is equal to 1 for Bihar and 0 for the other control states. Thus, the parameter of interest, β_k is the treatment on treated DID estiamte which shows the effect of IVRS on outcomes in districts of Bihar after the program has been implemented. Any secular unobserved changes in outcomes are controlled for under the standard difference-in-difference identifying assumption.

To allow for the impact of the policy change to evolve over time ,we estimate a difference-in-difference model with trend break to examine the impact of the program on enrollment and attendance.[13] The empirical model also allows differential trend between districts in Bihar and the control states allaying concerns over differential trend in outcome variables

$$\begin{aligned} y_{dt} = \gamma_0 + \gamma_1 \times \text{Bihar} \times (t - 2009) + \gamma_2 \times \text{Bihar} \times (t - 2012) + \gamma_3 \times \text{Bihar} \times \text{Post} + \\ \gamma_X X_{dt} + \tau_t + \delta_d + \varepsilon_{dt}. \end{aligned} \quad (10)$$

The DID coefficient γ_3 estimates the effect of the policy change for the entire post period, while $\gamma_1 + \gamma_2$ measures the change in the trend in outcome variables between Bihar and the control states.

6 Results

6.1 Main Results

We show our main results using three different datasets. The first two aid in understanding if there are any discrepancies in the assessment of beneficiary take-up based on state's official and independently collected data. The third sample is used to determine the impact on quality metrics based on independent assessments conducted by institutes engaged by the central government.

[12] Districts are the administrative unit under the state. Our control states are in close proximity of Bihar and have a comparable poverty profile.

[13] See Greenstone and Hanna (2014) and Burgess and Pande (2005) for a similar specification.

6.1.1 Independent Data Based Assessment

In Table 2, we use school level ASER data for Bihar with district fixed effects to conduct an event study analysis. In column 1, we estimate whether a school provides MDM or not. In the pre-policy years, this estimate is negligible and statistically insignificant. In 2012, there is a 17 percentage point increase in the likelihood of a school serving MDM. This effect is statistically significant at 1 percent significance level and persists in the first post policy year 2013. The pre-post comparison indicates an improvement of 18 percentage points. On a baseline average of 0.562, this is a 32 percent increase. This is robust to inclusion of school level controls reported in column 2.[14]

In column 3, we examine the effect on whether MDM was cooked on the day of the surprise visit by the survey team. Prior to the policy change, this estimate was also close to 0. This jumps to 0.19 in 2012 and persists at 14 percentage points in 2013 both significant at the 1 percent significance level. Comparison of pre-post coefficients indicate an improvement of 12 percentage points. This is a 24 percent increase over a base of 0.503. Again, the estimates are robust to including school level controls in column 4. Overall, we find consistent evidence that MDM provision in treatment schools improved after the policy was implemented.[15]

Next, we focus on our DID estimation and report the results in Table 3. Here, our sample includes 23,980 schools.[16] Our DID estimates are remarkably similar to the event study estimates reported in Table 2. For the first outcome whether a school provides MDM or not, the estimates in column 1 indicate interaction coefficients indistinguishable from 0 prior to the policy change, and an 17 percentage points increase in the likelihood of serving MDM in 2012 in Bihar districts, which persists at 16 and 14 percentage points in 2013 and 2014, respectively. All of these estimates are statistically significant at the 1 percent level. Results are robust to inclusion of school level controls in column 2. A pre-post difference in coefficients of 21 percentage points, on a baseline average of .562, indicates an improvement of 37 percent in the likelihood of provision of MDM in schools in Bihar.

Similarly, we find evidence of an increase in the likelihood of MDM being cooked on the day of the surprise visit by the survey team in the school in districts of Bihar. Point estimates in columns 4 reveal that the interaction coefficient for 2011 is negative -0.08, statistically significant at the 10 percent significance level. Then it changes sign and is estimated to be 0.17, significant at the 1 percent significance level in 2012. Subsequently, it is 0.14 and statistically significant at the 1 percent significance level in 2013. In 2014 the interaction coefficient estimated as 0.16 continues to be statistically significant at 1 percent level. A comparison of the interaction effects for the pre and post IVRS years indicate that the likelihood of MDM being

[14]These controls include indicators for blackboards in grade 2, drinking water facilities, toilets for girls and boys, and school type fixed effects.

[15]The number of observations is different in columns 1 and 3 because of missing values of outcome variables and further reduced in columns 2 and 4 due to missing values of control variables in the data.

[16]The data is a repeated cross section of schools in a district level panel data.

cooked on the day of inspection increased by 22 percentage points. On a baseline of .503, this is a 44 percent increase. The pre-post comparison of the interaction coefficients corroborates the findings in the event study analysis reported earlier.

6.1.2 Official (State Government) Data Based Assessment

Table 4 reports the results of our event study, where we compare district level official records related to mid-day meal provision before and after the policy change in Bihar. The baseline averages reported in columns 1 and 2 suggest that 100 percent of the primary and upper primary schools in Bihar were serving mid-day meals before 2012. However, in 2012, the year of the introduction of the IVRS program, the fraction of primary and upper primary schools serving meals dropped by 1 percent. The coefficient for primary schools is significant at 5 percent but it is statistically indistinguishable from 0 for upper primary schools. Compared to 2009, the fraction of primary schools serving meals dropped further by 1.4 and 3.5 percent in 2013 and 2014, respectively. Both these coefficients are highly statistically significant at 1 percent level. For upper primary schools, the decline in the fraction of schools serving meals during the second and third year of the program, reported in column 2, are measured at 14.4 and 10.6 percent, respectively. These estimates are also highly significant. A comparison of the pre-post coefficients reveals that after the introduction of the IVRS program the fraction of primary and upper primary schools serving mid-day meals fell by 1.4 and 14.5 percent, respectively.

In columns 3 and 4 we examine the fraction of enrolled students opting for mid-day meals as reported by the state government. We estimate the effects separately for primary and upper primary schools. According to the state government reports before the introduction of the program in 2012, all primary and upper primary students enrolled in government schools opted for mid-day meals. In 2012, however, 4.9 and 6.7 percent fewer students opted for meals in primary and upper primary schools, respectively. One year after the program, in 2013, the fraction of students availing mid-day meals dropped precipitously by 34 and 36.7 percent fewer students in primary and upper primary grades. These estimates are statistically significant at 1 percent level. In the last year of our data the drop in the fraction of students availing meals were more modest. Given the baseline at 100 percent, a comparison of the pre-post coefficients reveals that on average 34 and 36.7 percent fewer students availed mid-day meals in primary and upper primary schools after the policy change in Bihar.

In Table 5, we document the results for the DID analysis using additional data from 4 comparable neighboring states as controls.[17] Note that before 2012, the year IVRS was implemented, according to government reports all primary and upper primary schools in Bihar were proving mid-day meals. The interaction coefficients for 2010 and 2011, in column 1, implies that compared to 2009 the fraction of primary schools providing meals in the control states were marginally lower by 0.5 and 0.3 percent, respectively. This trend reversed in 2012 and one year

[17] The control states are Chattisgarh, Jharkhand, Orissa, and Madhya Pradesh.

after the policy change the interaction coefficient is -1.1 and it is significant at 5 percent level. For the last year of our data the interaction coefficient is largest at -3.4, significant at 1 percent level. The difference-in-difference estimate between 2011 and 2013 reported at the bottom of the table suggests that 1.3 percent fewer primary schools was providing meals in Bihar, and is significant at the 5 percent level. In column 2, for upper primary schools, we observe a similar pattern but the drop in the fraction of schools serving meals in Bihar is more prominent. The difference-in-difference estimate between 2011 and 2013 suggests that 16 percent fewer upper primary schools served meals in Bihar, and it is precisely estimated.

In the rest of the columns we report the interaction coefficients for the percentage of students enrolled in primary and upper primary schools availing mid-day meals. The estimates for the pre years vary between 4.3 to -0.1 but all of them are statistically indistinguishable from 0. The estimates drop to -10.8 and -17.2 for the year 2012 and fell sharply to -41.3 and -48.1 in the first post year in 2013 for primary and upper primary schools, respectively. The difference-in-difference estimates given by the difference between the pre-post interaction coefficients reported at the bottom are -41.2 and -45.8, they are statistically significant at 1 percent level.

Overall both event study and difference-in-difference estimates show similar trends in the provision of mid-day meals in Bihar. After the IVRS program the fraction of schools serving meals, according to the government records fell, whereas in contrast, independently collected data shows an improvement in provision of meals.

6.1.3 Food Grains and Cooking Costs

In Tables 6 and 7 we turn to examining other inputs such as rice and cooking costs which include costs of other materials used in meal preparation. We estimate the effects separately for primary and upper primary schools. Table 6 reports the estimates from an event study model for the state of Bihar. For primary schools, in column 1, consumption of rice in 2010 relative to 2009 was 344.1 metric tonnes higher but imprecisely measured. In 2011, the estimate was 31.2 and statistically indistinguishable from 0. In 2012, it was 550.9 and statistically significant at 1 percent level. This jumped significantly to 1437 in 2013, a year after the policy change. For 2014 the estimated coefficient is also precisely estimated at 1327. Similarly, for upper primary schools, this estimate is smaller and statistically insignificant in the pre-IVRS years and jumps to 430, significant at 1 percent, in 2012. Then it dramatically increases to 1245, significant at 1 percent level in the following year. A pre-post comparison of these coefficients indicates that consumption of rice increased by 1406 and 1130 metric tonnes at primary and upper primary schools in Bihar. Given the baseline average consumption levels this was an increase by 58 and 113 percent. These estimates suggesting increase in the costs producing mid-day meals is counter-intuitive as earlier we find that the fraction of schools serving meal are declining after the policy change.

Costs for cooking meals also show a similar pattern. For primary schools, in column 3, one year before the policy change the coefficient was 8.66, statistically significant at 10 percent. One year after, in 2013 it jumped to 64, statistically significant at the 1 percent level. For upper primary schools, in column 4, the estimates are also similar. A pre-post comparison of the coefficients on cooking costs indicate that cooking costs increased by 55.4 and 40.9 million Rs. in primary and upper primary schools, respectively. Given the baseline averages this is equivalent to a 83 and 140 percent increase in the cooking costs for primary and upper primary schools in Bihar.

In Table 7 we report the difference-in-difference estimates for inputs required to produce meals in Bihar and 4 neighboring states. Columns 1 and 2 reports year-wise interaction coefficients for consumption of rice in primary and upper primary schools. The interaction coefficients for rice in 2011, one year before the implementation of IVRS, are estimated at 10.1 and -88.7. However, none of them are statistically significant. In 2013, one year after the policy change in Bihar, the interaction coefficients are significant at 1 percent at 1479 and 926, respectively. A comparison of the pre- and post-IVRS coefficients, reported at the bottom panel, suggest that the after the policy change consumption of rice in Bihar increased by 61 and 101 percent for primary and upper primary schools in Bihar.

The rest of the columns in Table 7 show the DID estimates for cooking costs to prepare meals. We observe a declining trend in cooking costs for the pre-IVRS years in Bihar compared to the rest of the 4 states. The interaction coefficient decreased from 1.76 in 2010 to -10.9 for primary schools while it dropped from -16.5 to -20.2 for upper primary schools. Most of these coefficients are statistically significant. However, the trend breaks in 2012 and a pre-post comparison of the interactions are similar to the estimated differences in the event study analysis and they are statistically significant at 1 percent level. Cooking costs for primary schools in Bihar increased by 69 percent while it jumped by 107 percent in upper primary schools. These estimates are significant at 1 percent level.

6.1.4 Central Government Commissioned Audits Data Based Quality Assessment

The quality audit data contains an unbalanced panel of districts from 2010 to 2013 for the states in our sample and has a total of 180 district year observations. Hence, we are not able to estimate an event study empirical model due to the small number of observations per year. We show our condensed DID estimates in Table 8. Fraction of schools among the audited schools that served good quality meals increased post IVRS policy change increased in Bihar relative to other states. The point estimate is 0.47 implying a 47 percentage points improvement in Bihar (column 1). The coefficient is significant at the 1 percent significance level. This is commensurate with a decline in bad quality meals.[18] In column 2, bad quality meals declined by 67 percentage points. In column 3, we report the estimate for fraction of audited schools providing sufficient quantity of meals. This went up by 48 percentage points, statistically

[18] Since these measures in the reports are conducted from qualitatively assessments, both good and bad quality schools are reported.

significant at the 5 percent significance level. The fraction providing insufficient meals declined by 60 percentage points. The interaction coefficient is significant at the 1 percent significance level.

6.2 Enrollment, Attendance, and Test Scores

Despite negligible tuition fees primary school enrollment in India is not universal. The overhead costs of books, uniforms and other supplies could be substantially high discouraging poor families from sending their children to school (PROBE Team, 1999). Food for education program in Bangladesh (Ravallion and Wodon, 2000) and cooked meals in India (Afridi, 2011) has been shown to improve enrollment and attendance in schools. In this section we explore the effects of improvements in the mid-day meals in Bihar after the introduction of the IVRS.

6.2.1 Effects on Enrollment & Attendance

Table 9 reports the effects of IVRS on enrollment and attendance in public schools using the ASER survey data (2009–2014). Panel A reports the coefficients from a DID model with trend break outlined in equation 10 for enrollment in grades 1–5. In column 1 the coefficient measuring differential trend between districts in Bihar and rest of the states (γ_1) is -4.19 and is statistically significant at 1 percent. This suggests that enrollment in grade 1 in public schools in Bihar was declining at a faster rate compared to the rest of the states. However, this declining trend was arrested and reversed in 2012. The triple-interaction coefficient (γ_2) measures the magnitude of this reversal. The relative strength of these two coefficients 1.98 ($\gamma_1 + \gamma_2$), reported at the bottom panel is significant at 1 percent. Overall, the number of students enrolled in grade 1 (Panel B, column 1) in Bihar after the policy change declined by -6.03 (γ_3). Given the baseline enrollment figures this translates as a 9 percent drop in enrollment. For higher grades, reported in column 2 through 5, the coefficient on differential trend and trend break post-IVRS vary by magnitude and direction. However, the overall DID estimate of the effects of IVRS continue to be negative and statistically significant at 1 percent. The percentage drop is 12.5% for grade 2, 17% for grade 3, 21.7% for grade 4, and 22% for grade 5, respectively.

Panel B of Table 9 reports the estimates on attendance in public schools in grade 1 through 5. The coefficient on the interaction between Bihar dummy and time trend (γ_1) in column 1, measuring differential trend for Bihar for attendance in grade 1, is negative at -1.8 and it is statistically significant at 1 percent. However, this negative trend was broken in 2012 as the triple interaction coefficient (γ_2) is significant and positive at 1.4. The coefficient on the interaction between Bihar dummy and post-IVRS (γ_3), measuring the average change in attendance in grade 1 in Bihar after the policy change is 6.65 and it is significant at 1 percent. This accounts for a 17.5 percent increase in attendance from the baseline average in Bihar. The estimates for other grades reported in column 2 to 5 are similar. The percentage increase in attendance is 14% for grade 2, 17% for grade 3, 14% for grade 4, and 17% for grade 5, respectively.

6.2.2 Effects on Test Scores

Consumption of regular school meals can improve student participation in terms of regular attendance and increased attention by decreasing malnutrition. Vermeersch and Kremer (2005) estimate that daily feeding in Kenya led to a 30% increase in preschool participation rate. However, increased participation might be on account of the desire to receive food through the program as opposed to better health. Existing literature fails to distinguish the channels of increased participation resulting from school feeding programs. Our estimates show that the improved mid-day meal program in Bihar post-IVRS led to a decline in student performance suggesting that the improved attendance discussed earlier was most likely on account of the desire to receive meals.

Table A.4 reports the results of estimations on arithmetic and reading scores, described earlier in Section 4, using a DID model with trend break in 2012. The coefficients on the interactions between the Bihar dummy and time trend (γ_1) is positive and significant at 1 percent level for arithmetic (Panel A) and reading (Panel B) test scores for students in grades 1 through 5. This suggests that learning outcomes for students in Bihar compared to other states were improving significantly over time. Also note that the coefficients on the triple interaction (γ_2) is negative and outweighes the Bihar trend (γ_1) for both test scores and for all grades.

The DID estimates (γ_3) on test scores are negative for both arithmetic and reading tests. However, their magnitude and significance varies. For example, in column 1, for students in grade 1 in Bihar average arithmetic test decreased by 0.14 after the policy change. This estimate is significant at 5 percent and signify a 8 percent drop from the baseline average. Similar patterns are observed for students in other primary grades. The DID estimates for reading scores are negative and statistically significant for all grades. The percentage drop in reading test scores are measured at 10 for grade 1, 6 for grade 2, 8 for grade 3 and 4, and 6 for grade 5, respectively.

6.3 Selection and Endogeneity Concerns

One of the main empirical concerns might be that the districts of Bihar are trending differently and the results are confounded by these trends. We allay this concern for our independent assessment based results shown in Table 3 in two ways. First, we include district specific trends in our specifications. On inclusion of district specific trends, the results remain remarkably similar. Second, we match districts on observable school characteristics and estimate a generalized DID model on this sample.

We provide results in Table 10. In the first panel, we show our baseline specification results condensing years into pre (2009, 2010, and 2011) and post (2012, 2013, and 2014) policy change. We include a state specific trend in this specification in addition to the district and year fixed effects. Standard errors are clustered at the district level. Additionally, we control for average district school characteristics.[19] We find a 23 percentage points increase in the likelihood that the schools in the treated areas serve MDM post treatment (column 1), 27 percentage points increase in the likelihood that MDM was cooked on the day of the surprise visit (column 2). Both these estimates are statistically significant at the 1 percent significance level.

In the Panel B, we include the district specific trends. The results remain remarkably similar to the estimates reported in Panel A.

In addition, we match the districts using propensity scores which we calculate using the above mentioned control variable. We trim the observations which are outside the common support of the propensity score distribution. Figure A.1 shows the relative distributions for treated (Bihar) districts and the control (other states) districts and highlights the common support. In the third panel, we restrict the sample to this common support and estimate a DID model.[20] Our results, shown in the third panel, are very similar to the results documented in the first panel. In the last panel, we use a generalized DID method proposed by James J. Heckman (1997) to estimate the treatment effect. We use a kernel based matching algorithm and employ a gaussian kernel for the procedure. We present bootstrap standard errors. Our previous results are confirmed using this specification as well.

7 Conclusion

This paper studies the role of IT technology in improving transparency and accountability in public service delivery. We use the roll-out of a technology enabled monitoring mechanism (the Interactive Voice Response System or the IVRS) in the mid-day meal provision in Bihar, and show that a simple mechanism that aids in cross tallying the information provided by the middle tier of the delivery chain in welfare programs can reduce leakages and increase the efficacy of the programs. Using independently collected data, we find that the technology enabled policy change increases the likelihood of meal provision in a school in Bihar by 21 percentage points, and the likelihood of meal being cooked on the day of surprise visit to school by 20 percentage points. These results are robust to a number of specifications which include matching based difference-in-difference specifications, and control district specific trends. The increase in the take-up of the program by beneficiaries is also accompanied by an improvement in the quality and sufficiency of meals. Using trend break models with this same data, we find that enrollment in schools declined, whereas reported attendance increased significantly.

Using central government commissioned audits data, we find an increase of 47 percentage points in fraction schools serving good quality of meals in Bihar schools post IVRS and an

[19] We include district level school infrastructure such as fraction of schools in a district with tap or hand-pump for drinking water, common toilet, separate toilet for boys and girls, and boundary wall; and average number of appointed teachers, teachers present during the survey as controls.

[20] We show covariate balance in Table A.2.

increase of 48 percentage points in fraction of schools serving sufficient quantity meals. In contrast, using state official records, we find that the fraction of schools serving meals and among enrolled students the number of children availing MDM reduces post IVRS. Surprisingly, the amount of rice consumed and cooking costs in a district increase after the reform. Our results provide evidence that the IVRS resulted in reduction in leakage in the delivery system.

Our findings have important policy implications. This study demonstrates that a policy driven reform initiated by a state government succeeded in improving the delivery in of a very important public service. Hence, state capacity can be increased by reforming the existing public institutions. Second, these improvements might be portable to other arenas of public service delivery which have similar delivery channels such as the public distribution system.

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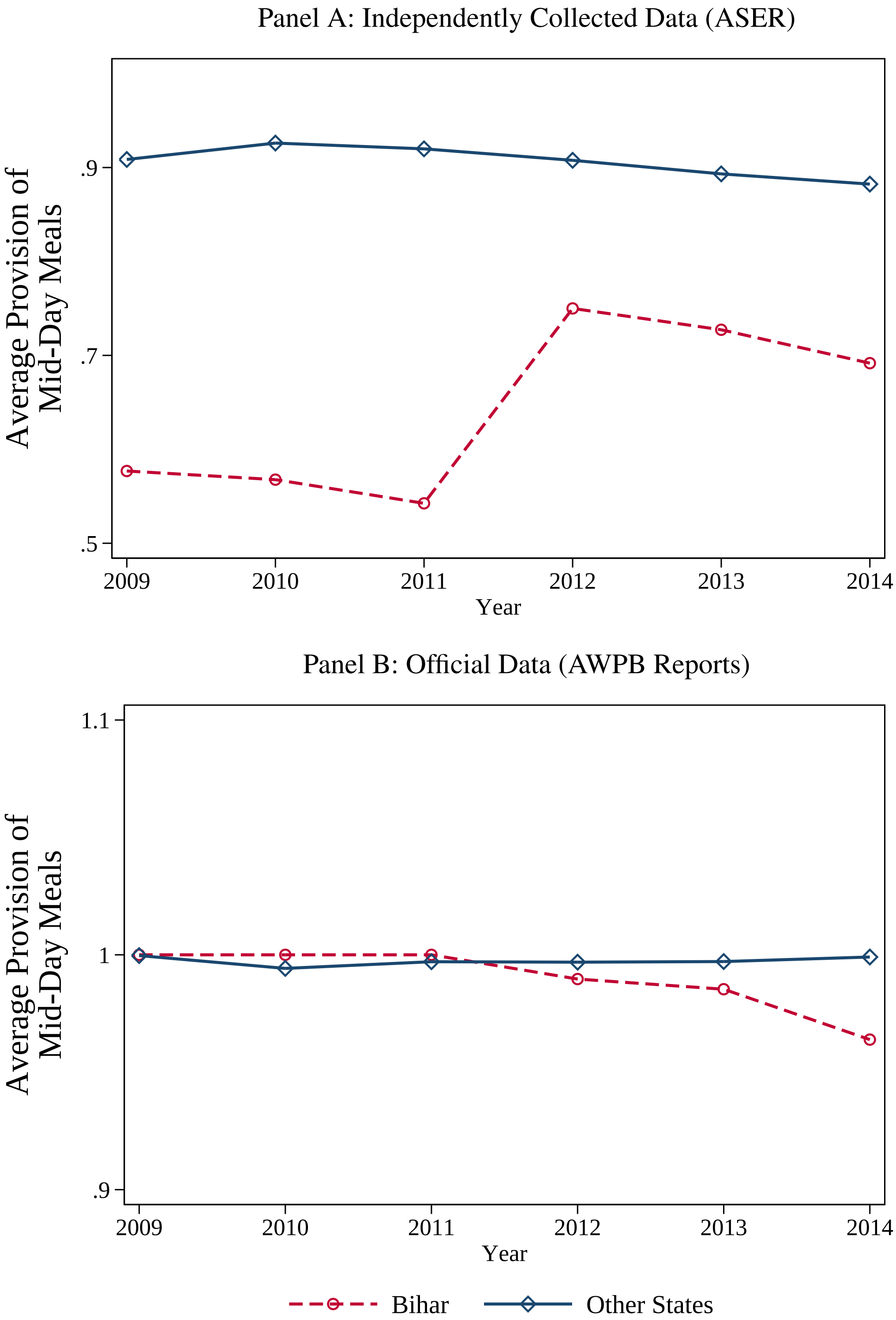
FIGURE 1: Fraction of Schools Serving Mid-Day Meals.



Notes: Independently collected school (primary and upper primary) level data are from the Annual Status of Education Reports (ASER). District level Annual Work Plan Budgets (AWPB) for primary and upper primary schools submitted to the Government of India by the state mid-day meal authorities constitute the source for official data. Other states include Jharkhand, Madhya Pradesh, Orissa and Chhattisgarh.

TABLE 1: Summary Statistics

	Bihar			All states		
	Obs	Mean	S.D.	Obs	Mean	S.D.
Panel A: AWPB Data.						
Percent of schools serving MDM: Primary	228	99.01	2.39	958	99.58	1.61
Percent of schools serving MDM: Upper Primary	189	90.81	24.34	851	97.20	13.60
Percent of students availing MDM: Primary	228	91.01	12.79	958	88.45	37.56
Percent of students availing MDM: Upper Primary	228	88.62	15.42	958	86.18	26.37
Rice consumption (in M.T.): Primary	228	2892.95	1438.61	958	1615.35	1383.53
Rice consumption (in M.T.): Upper Primary	228	1438.96	889.73	958	961.43	832.52
Cooking cost (in Million Rs.): Primary	228	89.58	49.23	958	62.41	38.14
Cooking cost (in Million Rs.): Upper Primary	228	45.36	31.02	958	36.65	24.41
Panel B: ASER School Level Data.						
School provides meals	6105	0.65	0.48	23980	0.84	0.37
Meals were cooked on the day of visit	6069	0.58	0.49	23781	0.73	0.44
Tap or hand-pump for drinking water	6153	0.93	0.25	24236	0.88	0.32
No. of teachers appointed	4815	2.76	2.85	18178	2.64	2.52
No. of teachers present	4815	2.23	2.29	18178	2.18	2.08
Common toilet in the school	4937	0.53	0.50	19576	0.48	0.50
Separate boys toilet in the school	5175	0.62	0.48	20335	0.60	0.49
Separate girls toilet in the school	5306	0.66	0.47	20740	0.65	0.48
School has boundary wall	6098	0.49	0.50	23977	0.42	0.49

Notes: District level Annual Work Panel Budgets (AWPB) used for Panel A for the years 2009–14. School and household survey data from Annual Status of Education Report (2009-14) used for Panel B. Other states include Jharkhand, Madhya Pradesh, Orissa and Chhattisgarh.

TABLE 2: Effect of Interactive Voice Response System (IVRS) on Mid-Day Meal Provision in Schools in Bihar using ASER Data

Dependent Var.	School Provides Meal		MDM Cooked	
Baseline average	.562	.562	.503	.503
	(1)	(2)	(3)	(4)
Two years before IVRS	-0.0063	-0.0088	0.036	0.046
	(0.04)	(0.04)	(0.04)	(0.04)
One year before IVRS	-0.035	-0.059	0.024	0.0048
	(0.04)	(0.04)	(0.04)	(0.04)
IVRS year	0.17***	0.14***	0.19***	0.15***
	(0.03)	(0.04)	(0.04)	(0.04)
One year after IVRS	0.15***	0.10**	0.14***	0.11**
	(0.04)	(0.04)	(0.05)	(0.05)
Two years after IVRS	0.11**	0.074*	0.15***	0.12***
	(0.04)	(0.04)	(0.05)	(0.04)
Post IVRS - Pre IVRS	.18***	.16***	.12**	.1**
School Characteristics	No	Yes	No	Yes
R Squared	0.067	0.069	0.074	0.081
No. of Observations	6105	4854	6069	4828

Notes: We use school level data from the Annual Status of Education Report (ASER) for the years 2009–2014. The sample is restricted to schools in the state of Bihar. All specifications control for district fixed effects. School characteristics include indicators for black boards in grade 2, tap or hand-pump for drinking water, availability of toilets for boys and girls and school type fixed effects. Standard errors are robust and clustered at the district level.

TABLE 3: Diff-in-Diff Estimate of Interactive Voice Response System (IVRS) on Mid-Day Meal Provision in Schools using ASER Data.

Dependent Var.	School Provides Meal		MDM Cooked	
Baseline average	.562	.562	.503	.503
	(1)	(2)	(3)	(4)
Bihar × 2010	-0.024	-0.030	-0.058	-0.061
	(0.04)	(0.04)	(0.04)	(0.04)
Bihar × 2011	-0.048	-0.064	-0.062	-0.083*
	(0.04)	(0.04)	(0.05)	(0.04)
Bihar × 2012	0.17***	0.16***	0.19***	0.17***
	(0.04)	(0.04)	(0.04)	(0.05)
Bihar × 2013	0.16***	0.14***	0.17***	0.14***
	(0.04)	(0.04)	(0.05)	(0.05)
Bihar × 2014	0.14***	0.12***	0.18***	0.16***
	(0.05)	(0.04)	(0.05)	(0.05)
Post IVRS - Pre IVRS	.21***	.2***	.24***	.22**
School Characteristics	No	Yes	No	Yes
R Squared	0.149	0.147	0.110	0.114
No. of Observations	23980	18798	23781	18667

Notes: We use school level data from the Annual Status of Education Report (ASER) for the years 2009–14. The sample is restricted to schools in the states of Bihar, Chattisgarh, Jharkhand, Madhya Pradesh, and Orissa. All specifications control for district and year fixed effects. School characteristics include indicators for black boards in grade 2, tap or hand-pump for drinking water, availability of toilets for boys and girls, and school type fixed effects. Standard errors are robust and clustered at the district level.

TABLE 4: Effect of Interactive Voice Response System (IVRS) on Mid-Day Meal Provision for Schools in Bihar using Official Data.

Dependent Variable	Percentage of Schools Serving MDM		Percentage of Enrolled Children Availing MDM	
	Primary	Upper Primary	Primary	Upper Primary
Baseline average	100	100	100	100
	(1)	(2)	(3)	(4)
Two years before IVRS	-0.00	0.07	-0.00	-0.00
	(0.25)	(1.78)	(0.31)	(0.57)
One year before IVRS	-0.00	0.07	-0.00	0.00
	(0.25)	(1.78)	(0.31)	(0.57)
IVRS year	-1.01**	-1.05	-4.91***	-6.74***
	(0.50)	(1.87)	(0.31)	(1.83)
One year after IVRS	-1.37***	-14.44***	-34.08***	-36.73***
	(0.43)	(3.37)	(1.01)	(1.19)
Two years after IVRS	-3.55***	-10.62***	-14.97***	-24.81***
	(0.42)	(3.56)	(0.55)	(0.57)
Post IVRS - Pre IVRS	-1.37***	-14.51***	-34.08***	-36.73***
R Squared	0.451	0.464	0.956	0.890
No. of Observations	228	180	228	228

Notes: District level annual data used from the Ministry of Human Resource Development for the years 2009–14. The sample is restricted to the state of Bihar. All specifications control for district fixed effects. Standard errors are robust and clustered at the district level.

TABLE 5: Diff-in-Diff Estimate of Interactive Voice Response System (IVRS) on Mid-Day Meal Provision for Schools in Bihar using Official Data.

Dependent Variable	Percentage of Schools Serving MDM		Percentage of Enrolled Children Availing MDM	
	Primary	Upper Primary	Primary	Upper Primary
Baseline average	100	100	100	100
	(1)	(2)	(3)	(4)
Bihar × 2010	0.54**	0.50	4.30	0.70
	(0.24)	(1.20)	(8.99)	(5.41)
Bihar × 2011	0.27**	1.95	-0.11	-2.33
	(0.12)	(1.75)	(8.13)	(4.62)
Bihar × 2012	-0.71	1.77	-10.8**	-17.2***
	(0.55)	(1.58)	(5.37)	(4.55)
Bihar × 2013	-1.06**	-14.2***	-41.3***	-48.1***
	(0.52)	(4.07)	(4.54)	(3.41)
Bihar × 2014	-3.38***	-10.3**	-27.5***	-42.1***
	(0.52)	(4.17)	(3.60)	(2.67)
Post IVRS - Pre IVRS	-1.33**	-16.11***	-41.23***	-45.81***
R Squared	0.397	0.383	0.393	0.395
No. of Observations	958	842	958	958

Notes: District level annual data used from the Ministry of Human Resource Development for the years 2009–14. The sample is restricted to the state of Bihar. All specifications control for districts fixed effects and state specific time trends. Standard errors are robust and clustered at the district level.

TABLE 6: Effect of Interactive Voice Response System (IVRS) on Rice Consumption and Cooking Costs in Bihar using Official Data.

Dependent Variable	Rice Consumed (in M.T.)		Cooking Cost (in Million Rs.)	
	Primary	Upper Primary	Primary	Upper Primary
Baseline average	2403.04	997.48	66.28	29.19
	(1)	(2)	(3)	(4)
Two years before IVRS	344.1	83.0	13.9**	0.22
	(220.29)	(86.22)	(6.33)	(3.29)
One year before IVRS	31.2	114.9	8.66*	3.16
	(185.60)	(119.76)	(4.89)	(3.77)
IVRS year	550.9***	429.6***	29.8***	15.5***
	(172.84)	(96.69)	(4.93)	(3.12)
One year after IVRS	1437.0***	1244.9***	64.0***	44.1***
	(254.63)	(169.73)	(8.18)	(5.63)
Two years after IVRS	1326.9***	1172.2***	68.5***	47.0***
	(259.03)	(169.99)	(8.91)	(6.14)
Post IVRS - Pre IVRS	1405.79**	1130.01***	55.38***	40.89***
R Squared	0.721	0.746	0.762	0.763
No. of Observations	228	228	228	224

Notes: District level annual data used from the Ministry of Human Resource Development for the years 2009–14. The sample is restricted to the state of Bihar. All specifications control for district fixed effects. Standard errors are robust and clustered at the district level.

TABLE 7: Diff-in-Diff Estimate of Interactive Voice Response System (IVRS) on Rice Consumption and Cooking Costs using Official Data.

Dependent Variable	Rice Consumed (in M.T.)		Cooking Cost (in Million Rs.)	
	Primary	Upper Primary	Primary	Upper Primary
Baseline average	2403.04	997.48	66.28	29.19
	(1)	(2)	(3)	(4)
Bihar × 2010	306.2	-135.4	1.76	-16.5***
	(239.29)	(103.25)	(6.74)	(3.65)
Bihar × 2011	10.1	-88.7	-10.9*	-20.2***
	(215.11)	(136.94)	(5.59)	(4.27)
Bihar × 2012	700.2***	161.6	7.50	-13.6***
	(222.00)	(124.35)	(6.56)	(4.24)
Bihar × 2013	1479.3***	925.8***	34.7***	11.2*
	(297.98)	(197.61)	(9.55)	(6.68)
Bihar × 2014	1397.9***	922.7***	48.1***	25.5***
	(299.91)	(192.28)	(10.32)	(7.09)
Post IVRS - Pre IVRS	1469.18***	1014.56***	45.52***	31.43***
R Squared	0.879	0.862	0.863	0.835
No. of Observations	841	841	958	954

Notes: District level annual data used from the Ministry of Human Resource Development for the years 2009–14. The sample is restricted to the state of Bihar. All specifications control for districts fixed effects and state specific time trends. Standard errors are robust and clustered at the district level.

TABLE 8: Effect of the Interactive Voice Response System on Meal Quality and Quantity

Dependent Variable	Fraction of Schools Observed Serving			
	Good Quality Meals (1)	Bad Quality Meals (2)	Sufficient Quantity Meals (3)	Insufficient Quantity Meals (4)
Bihar × Post	0.47***	-0.67***	0.48**	-0.60***
	(0.02)	(0.03)	(0.11)	(0.07)
R Squared	0.339	0.576	0.562	0.610
No. of Observations	180	180	180	180

Notes: We use district level monitoring data from the Ministry of Human Resource Development for the period 2010-13. The sample is restricted to the states of Bihar, Jharkhand, Orissa, Madhya Pradesh and Chhattisgarh. All specifications control for state and quarter fixed effects, district level school characteristics such as fraction of schools with toilet for boys and girls, drinking water facility, a boundary wall; and average number of teachers by gender. Standard errors are robust and clustered at the state level. IVRS was introduced in Bihar in the year 2012.

TABLE 9: Effect of Interactive Voice Response System (IVRS) on Enrolment and Attendance.

	(1)	(2)	(3)	(4)	(5)
Grade	1	2	3	4	5
Panel A: Enrollment from School Registers (ASER)					
Baseline average	68.02	67.94	69.63	66.16	61.1
Bihar $\times$ (t - 2009) [γ_1]	-4.19***	-0.91	0.67	3.43***	4.27***
	(1.29)	(1.25)	(1.32)	(1.09)	(1.21)
Bihar $\times$ (t - 2012) $\times$ Post 2012 [γ_2]	6.17***	2.57*	-0.72	-3.01*	-2.60*
	(1.48)	(1.55)	(1.82)	(1.52)	(1.55)
Bihar $\times$ Post 2012 [γ_3]	-6.03**	-8.53***	-12.0***	-14.4***	-13.4***
	(2.56)	(2.36)	(2.60)	(2.63)	(2.85)
R Squared	0.414	0.430	0.417	0.418	0.385
No. of Observations	18571	18574	18607	18591	18502
$\gamma_1 + \gamma_2$	1.98	1.66	-0.05	0.42	1.68
p-value	0.00	0.03	0.96	0.60	0.03
Panel B: Classroom Attendance (ASER)					
Baseline average	38.53	36.39	36.68	34.76	32
Bihar $\times$ (t - 2009) [γ_1]	-1.79***	-1.45**	-2.01***	-1.40***	-1.65***
	(0.63)	(0.60)	(0.54)	(0.51)	(0.53)
Bihar $\times$ (t - 2012) $\times$ Post 2012 [γ_2]	1.39**	1.00	1.06*	0.14	0.49
	(0.68)	(0.63)	(0.62)	(0.58)	(0.62)
Bihar $\times$ Post 2012 [γ_3]	6.65***	5.02***	6.06***	4.75***	5.42***
	(1.29)	(1.43)	(1.30)	(1.30)	(1.30)
R Squared	0.763	0.715	0.690	0.690	0.686
No. of Observations	18571	18574	18607	18591	18502
$\gamma_1 + \gamma_2$	-0.39	-0.45	-0.95	-1.26	-1.16
p-value	0.28	0.18	0.01	0.00	0.01

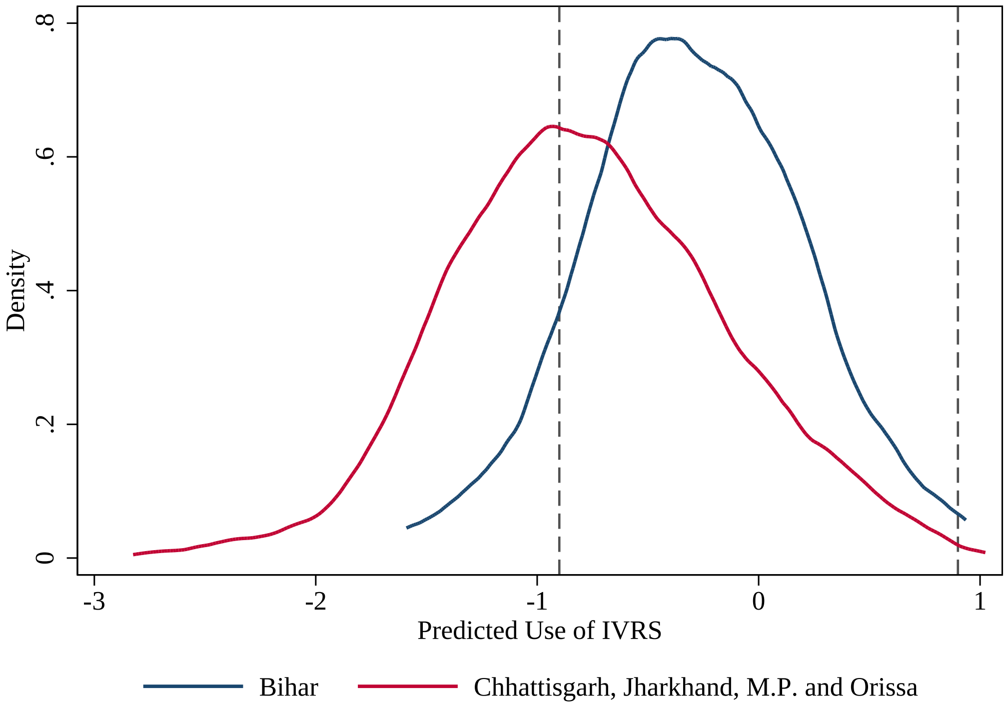
Notes: We use school level data from the Annual Status of Education Report (ASER) for the years 2009–2014. The sample is restricted to the states of Bihar, Chattisgarh, Jharkhand, Madhya Pradesh and Orissa. All specifications control for district fixed effects. School characteristics include indicators for black boards in grade 2, tap or hand-pump for drinking water, availability of toilets for boys and girls and school type fixed effects. Standard errors are robust and clustered at the district level.

TABLE 10: Robustness Check: Effect of IVRS on Mid-Day Meals

Dependent Var.	School Provides Meal (1)	MDM Cooked (2)
Panel A: Diff-in-Diff with all Districts		
Bihar × Post	0.23***	0.27***
	(0.05)	(0.05)
R Squared	0.651	0.570
No. of Observations	891	891
Panel B: Diff-in-Diff with District Specific Time Trends		
Bihar × Post	0.23***	0.26***
	(0.06)	(0.06)
R Squared	0.760	0.691
No. of Observations	891	891
Panel C: Diff-in-Diff with Districts on the Common Support		
Bihar × Post	0.26***	0.28***
	(0.05)	(0.06)
R Squared	0.691	0.616
No. of Observations	583	583
Panel D: Diff-in-Diff with Kernel based Propensity Score Matching		
Bihar × Post	0.18***	0.24***
	(0.03)	(0.03)
R Squared	0.508	0.322
No. of Observations	888	888

Notes: We use school level data from the Annual Status of Education Report (ASER) collapsed at the district level, for the years 2009–2014. The sample is restricted to the states of Bihar, Chattisgarh, Jharkhand, Madhya Pradesh and Orissa. All specifications in Panel A and B control for the variables as in Table A.1. and state specific time trends, district and year fixed effects. Standard errors are robust and clustered at the district level. In Panel C we use the Gaussian kernel and the standard errors are bootstrapped.

FIGURE A.1: Common Support in Predicted Probability of Use of IVRS



Notes: .

TABLE A.1: Percentage of Headmasters with Mobile Phones in Bihar.

District	Fraction of Headmasters with Mobiles
Araria	0.99
Arwal	1
Aurangabad	0.99
Banka	0.99
Begusarai	0.99
Bhagalpur	0.99
Bhojpur	0.99
Buxar	0.99
Darbhanga	0.99
Gaya	0.99
Gopalganj	0.99
Jamui	0.99
Jehanabad	0.99
Kaimur (Bhabua)	0.99
Katihar	0.99
Khagaria	0.99
Kishanganj	0.97
Lakhisarai	0.99
Madhepura	0.99
Madhubani	0.98
Munger	1
Muzaffarpur	0.9
Nalanda	0.99
Nawada	0.99
Pashchim Champaran	0.9
Patna	0.98
Purnia	0.99
Purvi Champaran	0.99
Rohtas	0.99
Saharsa	0.99
Samastipur	0.99
Saran	0.99
Sheikhpura	1
Sheohar	0.9
Sitamarhi	0.99
Siwan	0.99
Supaul	1
Vaishali	0.99

Notes: We use school level data from the Bihar Mid-Day meal Department.

TABLE A.2: Covariate Balance

	Control		Bihar				
	Obs. (1)	Avg. (2)	Obs. (3)	Avg. (4)	Diff. (5)	t-stat (6)	p-values (7)
Panel A: Districts on the Common Support							
Tap or hand-pump for drinking water	122	0.904	80	0.912	0.008	0.86	0.3883
No. of Teachers appointed	122	2.863	80	3.092	0.229	1.6	0.1105
No. of Teachers present	122	2.39	80	2.523	0.133	1.06	0.2887
Common toilet in the school	122	0.596	80	0.633	0.037	1.38	0.1681
Separate boys toilet in the school	122	0.512	80	0.508	-0.004	0.14	0.8883
Separate girls toilet in the school	122	0.531	80	0.521	-0.011	0.38	0.7053
School has boundary wall	122	0.461	80	0.489	0.028	1.38	0.1689
Panel B: Propensity Score Weighted Covariate Balance							
Tap or hand-pump for drinking water	331	0.907	111	0.902	-0.004	0.6	0.5517
No. of Teachers appointed	331	3	111	3.105	0.105	0.94	0.3489
No. of Teachers present	331	2.471	111	2.511	0.04	0.43	0.6697
Common toilet in the school	331	0.613	111	0.618	0.005	0.28	0.7763
Separate boys toilet in the school	331	0.521	111	0.518	-0.003	0.15	0.8839
Separate girls toilet in the school	331	0.544	111	0.53	-0.014	0.66	0.5096
School has boundary wall	331	0.47	111	0.467	-0.003	0.18	0.8554

Notes: We use school level data from the Annual Status of Education Report (ASER) collapsed at the district level, for the years 2009–13. The sample is restricted to the states of Bihar, Chattisgarh, Jharkhand, Madhya Pradesh and Orissa.

TABLE A.3: Effect of Interactive Voice Response System (IVRS) on mid-day meal provision in Schools in Bihar by Mobile Ownership by Headmasters.

Dependent Var.	School Provides Meal		MDM Cooked	
Baseline average	.562	.562	.503	.503
Bihar × 2010 × High Mobile Penetration	-0.041	-0.0094	-0.13*	-0.10
	(0.07)	(0.07)	(0.07)	(0.08)
Bihar × 2011 × High Mobile Penetration	-0.095	-0.073	-0.18**	-0.15*
	(0.08)	(0.08)	(0.08)	(0.08)
Bihar × 2012 × High Mobile Penetration	0.025	0.074	0.046	0.089
	(0.07)	(0.07)	(0.08)	(0.08)
Bihar × 2013 × High Mobile Penetration	-0.018	0.031	0.012	0.050
	(0.08)	(0.09)	(0.09)	(0.09)
Bihar × 2014 × High Mobile Penetration	-0.061	-0.0076	-0.063	-0.023
	(0.09)	(0.08)	(0.09)	(0.09)
Post IVRS - Pre IVRS	.08	.1***	.19*	.2**
School Characteristics	No	Yes	No	Yes
R Squared	0.150	0.148	0.111	0.115
No. of Observations	23980	18798	23781	18667

Notes: We use school level data from the Annual Status of Education Report (ASER) for the years 2009–2014. The sample is restricted to the states of Bihar, Chattisgarh, Jharkhand, Madhya Pradesh and Orissa. All specifications control for district fixed effects. School characteristics include indicators for black boards in grade 2, tap or hand-pump for drinking water, availability of toilets for boys and girls and school type fixed effects. Standard errors are robust and clustered at the district level.

TABLE A.4: Effect of Interactive Voice Response System (IVRS) on Test Scores for Students in Public Schools.

Grade	(1) 1	(2) 2	(3) 3	(4) 4	(5) 5
			Panel A: Arithmetic Test		
Baseline average	1.78	2.51	3.14	3.7	4.09
Bihar × (t - 2009) [γ_1]	0.17***	0.13***	0.21***	0.23***	0.25***
	(0.03)	(0.03)	(0.04)	(0.04)	(0.04)
Bihar × (t - 2012) × Post 2012 [γ_2]	-0.21***	-0.18***	-0.29***	-0.24***	-0.28***
	(0.04)	(0.04)	(0.05)	(0.05)	(0.05)
Bihar × Post 2012 [γ_3]	-0.14**	-0.086	-0.15	-0.21***	-0.18**
	(0.06)	(0.08)	(0.09)	(0.08)	(0.08)
R Squared	0.152	0.154	0.205	0.232	0.224
No. of Observations	59993	55869	56553	52612	58026
$\gamma_1 + \gamma_2$	-0.04	-0.04	-0.08	-0.01	-0.03
p-value	0.04	0.08	0.00	0.69	0.34
			Panel B: Reading Test		
Baseline average	1.76	2.52	3.17	3.78	4.18
Bihar × (t - 2009) [γ_1]	0.18***	0.14***	0.24***	0.22***	0.23***
	(0.03)	(0.04)	(0.04)	(0.04)	(0.04)
Bihar × (t - 2012) × Post 2012 [γ_2]	-0.23***	-0.21***	-0.33***	-0.24***	-0.25***
	(0.04)	(0.04)	(0.05)	(0.05)	(0.05)
Bihar × Post 2012 [γ_3]	-0.17**	-0.15*	-0.26**	-0.29***	-0.24***
	(0.07)	(0.09)	(0.10)	(0.09)	(0.09)
R Squared	0.160	0.151	0.172	0.174	0.153
No. of Observations	60423	56142	56782	52837	58190
$\gamma_1 + \gamma_2$	-0.05	-0.06	-0.09	-0.01	-0.02
p-value	0.01	0.02	0.00	0.68	0.53

Notes: We use school level data from the Annual Status of Education Report (ASER) for the years 2009–2014. The sample is restricted to the states of Bihar, Chattisgarh, Jharkhand, Madhya Pradesh and Orissa. All specifications control age and gender of the child, parents' age and years of education and district fixed effects. Standard errors are robust and clustered at the district level.

TABLE A.5: Effect of Interactive Voice Response System (IVRS) on Test Scores for Students in Private Schools.

Grade	(1) 1	(2) 2	(3) 3	(4) 4	(5) 5
		Panel A: Arithmetic Test			
Baseline average	2.6	3.39	3.93	4.22	4.48
Bihar × (t - 2009) [γ_1]	0.12**	0.062	0.27***	0.25***	0.18***
	(0.05)	(0.06)	(0.08)	(0.06)	(0.05)
Bihar × (t - 2012) × Post 2012 [γ_2]	-0.0071	0.092	-0.24**	-0.086	-0.11
	(0.08)	(0.08)	(0.10)	(0.08)	(0.09)
Bihar × Post 2012 [γ_3]	0.022	-0.050	-0.20	-0.35**	-0.16
	(0.12)	(0.16)	(0.17)	(0.17)	(0.17)
R Squared	0.242	0.239	0.233	0.212	0.185
No. of Observations	10588	9258	7713	6828	6582
$\gamma_1 + \gamma_2$	0.11	0.15	0.03	0.16	0.08
p-value	0.06	0.01	0.59	0.01	0.33
		Panel B: Reading Test			
Baseline average	2.63	3.45	4.06	4.3	4.54
Bihar × (t - 2009) [γ_1]	0.19***	0.072	0.25***	0.15**	0.10**
	(0.06)	(0.07)	(0.07)	(0.07)	(0.05)
Bihar × (t - 2012) × Post 2012 [γ_2]	0.026	0.16*	-0.18**	0.12	-0.021
	(0.09)	(0.09)	(0.08)	(0.10)	(0.07)
Bihar × Post 2012 [γ_3]	-0.12	-0.15	-0.27*	-0.39**	-0.055
	(0.14)	(0.17)	(0.16)	(0.17)	(0.15)
R Squared	0.235	0.192	0.150	0.132	0.103
No. of Observations	10628	9288	7748	6845	6590
$\gamma_1 + \gamma_2$	0.22	0.23	0.07	0.27	0.08
p-value	0.00	0.00	0.20	0.00	0.23

Notes: We use school level data from the Annual Status of Education Report (ASER) for the years 2009–2014. The sample is restricted to the states of Bihar, Chattisgarh, Jharkhand, Madhya Pradesh and Orissa. All specifications control age and gender of the child, parents' age and years of education and district fixed effects. Standard errors are robust and clustered at the district level.