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Regular Article

Information Bypass: Using Low-cost technological innovations to curb leakages in welfare programs[☆]

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ABSTRACT

Distribution networks entrusted to run welfare programs can have enduring leakages due to the expensive monitoring of agents at several echelons. This paper features a technological innovation harnessing low-cost computing that can help to curb leakages and reduce inefficiencies in such complex welfare distribution networks. A phone-based 'Interactive Voice Response System' that requires the last-mile distribution agents to report the number of beneficiaries at a very high frequency concurrently with business-as-usual beneficiary information reporting by the middle-tier delivery agents serves as a mechanism for increasing accountability. Using the roll-out of this system, we demonstrate that this innovation reduced leakage in school lunch provision in Bihar, India. While independently collected data highlights improvements in delivery, official statistics indicate a decline in the school lunches provision. We use within Bihar cellular towers location to bolster our identification in an instrumental variable framework.

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). The hierarchical organization of distribution networks, involving the flow of goods, services, and information across a multitude of levels and agents at many echelons, makes addressing agency problems a complicated endeavor. Agents at different levels, intermediaries and last mile could all be stealing from the system in a coordinated way or independently. Alternatively, some agents may not be stealing at all. From an agency theory perspective, the principal does not have cost-effective tools to establish the integrity of the information being provided by the multiple agents in the hierarchy and cannot directly observe these agents' efforts. Hence, complete contracts cannot be stipulated. This results in inefficiencies affecting the beneficiaries adversely.

In this paper, we study the consequences of an innovative mechanism designed to curb leakages in such environments. This mechanism operates by obtaining beneficiary take-up information from two sources: first, the beneficiary data is obtained daily and directly from the last-mile delivery agents using a low-cost integrated voice recording system; second, it is obtained with quarterly periodicity from the status quo official channels. Collecting the same information from dual sources in the same distribution chain enables the government to check co-opting of agents by making it costly. Delivery is further improved by augmenting field inspections with high-frequency data, which could deter malfeasance and improve enforcement efforts as enforcement agents might have timely actionable data.

This mechanism was launched by the government of Bihar in 2012 to improve the delivery of mid-day meals (MDM) in government schools.[1] Prior to this, anecdotal evidence pointed to widespread leakage from the MDM. Leakages in welfare programs targeted toward

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[1] The MDM is the world's largest school feeding program.

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children's health, nutrition, and education can have far-reaching intergenerational consequences. Significant malnourishment among children results in adverse health and education outcomes.[2] Enduring leakages from school feeding programs can undermine the public investment to combat malnourishment.[3]

A key challenge faced by the directorate of the MDM before 2012 was their reliance on the beneficiary take-up estimates provided by the middle-level delivery agents to determine the program's future allocations and performance. Such estimates were often non-verifiable and potentially rigged. To address this, the government introduced an ICT reform called 'Dopahar' which automatically called one of the five designated teachers chosen randomly from each school in Bihar daily and sought information about the take-up of the meals. We utilize the state-wide rollout of this program and official state-government reports, along with independently collected data from central government assessment teams and an independent NGO, Pratham, to analyze the impact of this reform on the MDM program. First, we compare the outcomes in the districts of Bihar with districts in the neighboring states before and after the introduction of the program. As per State official data, 100 percent of primary and upper primary schools in Bihar provided school meals before the introduction of the *Interactive Voice Response System* or IVRS system. However, after the introduction of the program, we detect a statistically significant decline in the reported fraction of schools serving MDM. As per the official data, the percentage of enrolled students availing meals declined by 34 and 37 percent, respectively, for primary and upper primary schools in Bihar after the IVRS reform. This indicates the deliberate use of 'ghost students' in the pre-IVRS regime to inflate the number of beneficiaries. Assessment using independent data sources collected during surprise visits to the schools, on the other hand, revealed significant improvements in take-up, sufficiency, and quality of meals. These results are robust to several specifications, including controls for school characteristics, district-specific trends, and a generalized DID, where we match districts based on observables before implementing the estimates. We also implement the synthetic difference-in-differences which clubs the benefits of both synthetic control and difference-in-differences methods and find consistent results. We provide estimates of leakage in the program by identifying the change in the number of beneficiaries taking up the program and find large savings.

Since the reform was introduced state-wide in Bihar, one concern might be that the administration was cracking down on corruption. In order to demonstrate that IVRS calls and not Bihar-specific policies were responsible for the improvements in the mid-day meal program, we use an instrumental variable approach where we use the roll-out of government-sponsored mobile towers as an instrument for IVRS call completion. The Indian government provided cell coverage to the underserved areas where private telecommunication providers did not deliver their services under a country-wide program. We use the location of the cell towers constructed under this policy (exogenous to local conditions), pre-determined location of all schools in Bihar, and village-level mobile coverage data to construct our instrument. We condition on population, the ruggedness of terrain, and elevation, the factors influencing location choice for the new towers. The towers were already constructed before the IVRS was rolled out. Hence, in addition to the previous controls, we condition on district and time-fixed effects and district-specific trends to net out changes that happened due to the roll-out of the cell towers. Our instrumental variable approach corroborates our reduced form findings. A one percent increase in call intensity (number of completed calls over the total calls made to a school during a month) increased the meal delivery by 0.825 percentage points.

Our cost–benefit analysis uses the estimated decrease in the beneficiaries and the cost of meals and finds that the system resulted in a gross saving of Rs. 85.5 million a year due to the curbing of leakages. In contrast, it costs Rs. 6 million annually in operating costs, thereby generating Rs. 79.5 million in net savings. This makes the IVRS mechanism viable and sustainable over the long haul.

A growing body of research has investigated the effectiveness of low-cost monitoring or other mechanisms in improving public service delivery. Technology-based monitoring by beneficiaries coupled with non-linear incentives has been demonstrated to be effective at inducing agents to exert effort (Duflo et al., 2012); mobile-based monitoring has been investigated as a lever to increase teacher accountability (Aker and Ksoll, 2019); but this mechanism cannot work in a setting where there is a hierarchy of agents who can be co-opted to steal from the system and efficiency is undermined explicitly by corrupt activity as in our context.

Both encouraging communities to hold public service providers accountable (Björkman and Svensson, 2009) and newspaper campaigns providing information to citizens can increase accountability (Reinikka and Svensson, 2005). Informal networks may also facilitate monitoring and enforcement (Nagavarapu and Sekhri, 2015). All these approaches rely on top-down information dissemination to beneficiaries. In contrast, the mechanism we study involves bottom-up information acquisition from randomly chosen last-mile delivery agents to disarticulate corruption ensconced at the last mile of the multiple-agent delivery chain. The former requires the collection of large swathes of data and information to be delivered to the beneficiaries, which can be very expensive. Collecting succinct information through an automatic ICT-enabled system from the last-mile agents can be much more cost-effective. This may reduce the bureaucratic collusion among multiple agents and reduce the possibilities of fraud and malfeasance.

Another notable contribution of our paper is to propose a technology- and data-based system that can increase state capacity in monitoring welfare programs.[4] Muralidharan et al. (2016) show that payment infrastructures can be improved using biometric payment cards; Banerjee et al. (2020) show that transparency in the fiscal transfer systems can reduce corruption; Muralidharan et al. (2021) show that last mile agents who embezzle from programs are responsive to the threat of a mobile phone auditing by the beneficiaries. Their study provides information to the beneficiaries posing a threat to the service providers. Our paper extends this nascent area of research 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. By acquiring information from multiple agents within the distribution channel, the coordination cost can be increased sufficiently to reduce leakages.

While providing information to beneficiaries as in Muralidharan et al. (2021) can make the last mile agents responsive, it requires actions by the beneficiaries. In settings where the elite benefit from corrupt practices, such as food distribution programs, an average beneficiary may not take any action (such as report misconduct) despite getting the information due to fear of retaliation. Also, what information to provide in which setting makes it context-specific. An advantage of acquiring the information from the last mile agent and using it to streamline leakages by breaking the nexus of co-opting agents is that it is free of reliance on beneficiaries' actions or the context sensitivity of the welfare programs.

Finally, our study complements and extends the literature on school feeding programs in developing countries. Jacoby (2002) examines

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

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

[4] In many countries, institutional capacity to implement safety net programs successfully is diminutive to the point of being deemed "failing" (Pritchett, 2009). As a result, development outcomes tied to the public institutions that deliver them are undermined.

the impact of the availability of school-based food programs on the feeding behavior of parents at home using data from the Philippines. The study found that parents do not cut back on the 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 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 school feeding programs, thereby increasing school attendance.

The 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. We provide a conceptual framework in Section 3. Section 4 discusses our data sources. In Section 5, we provide a discussion of our estimation strategy. Section 6 discusses the results and the robustness tests. Section 7 distills the cost–benefit analysis. Section 8 discusses alternative hypotheses. Section 9 concludes.

2. Background

2.1. MDM program and subsidies

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 all 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 child enrolled in a government or government-aided school to a meal on the school premises each school day.[5] Currently, the program covers all primary and upper primary government and government-aided schools, including *Madarsas* and *Maqtabs*. 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, anecdotal evidence points out that this program is fraught with corruption and inefficiencies. Improving the effectiveness of this program can potentially induce better nutrition and education outcomes for millions of children.

In the fiscal year 2015–16, the central and state governments spent a total of Rs. 99.12 billion (USD 1.59 billion) on the mid-day meal program, making it one of the largest welfare programs funded by the government.[6] The extent of the subsidies and the design of the program lends itself to large-scale leakages. The subsidy is intended to absorb both recurring and non-recurring costs of providing meals. Recurring costs include expenditures on food grains, ingredients, wages to cooks, helpers, and inspectors who audit the program. Non-recurring costs cover infrastructure, such as constructing kitchen sheds and procuring utensils. The expenditure is shared between the central and the state governments. The central government covers all non-recurring costs, foodgrains, and monitoring costs, while the remaining cost is shared between the center and the states in a 75:25 ratio. Typically, recurring grants are based on school-level consumption and, therefore, vary by school. Schools estimate and report their beneficiaries based on the number of students consuming meals and the number of expected working days in a month. This information is aggregated at the block (district subdivision), district, and state levels. Based on these aggregated reports, state governments prepare Annual Work Plans and Budgets (AWP&B) and submit them to the Project Approval Board (PAB) of the Ministry of Human Resource Development (MHRD) for review and approval. PAB approvals determine actual allocations and the release of funds.

2.2. Flow of beneficiary information

Panel A in Fig. 2 illustrates the flow of information from schools to the mid-day meal directorate prior to 2012. The schools submitted their requirements to the Block Resource Person (BRP). These requisitions include the number of beneficiaries, current status, and future requirements of funds and food grains in the school. The BRP submitted the collated data to the district manually each month. The district office reported this information to the directorate. Subsequently, the directorate made allocations that flowed back to the school through the same distribution channel based on the requisition. The districts issued allotments of funds and foodgrains to the blocks, and the responsibility to distribute the allotment to the schools rested with the BRPs. There was a significant scope of siphoning both funds and foodgrains from this system due to the lack of verification of information provided at several echelons of the distribution chain. Leakages could take the form of embezzlement of funds and foodgrain or reporting of inflated beneficiary numbers by the school teachers and other administrative officers. A case study by the Directorate of MDM (2013) acknowledges that

> "Data on how many requisitions were submitted and how many were processed, and figures on student attendance, number of beneficiaries and other key indicators on coverage, meals served, ⋯ were found to be inflated and inaccurate, but there were no means to authenticate the data ⋯"

2.3. Introduction of the IVRS in 2012

In 2012, the Directorate of MDM implemented *Dopahar*, an Interactive Voice Response System (IVRS) that collected real-time data directly to improve assessment and monitoring of school-level provision of meals on a real-time basis from the school teachers in the state of Bihar. In Fig. 2, Panel B, we depict the reform in information flow. Note that the only change to the pre-reform system was an additional information flow directly from the schools to the Directorate.

IVRS is a simple technology-enabled mechanism that helps to collect high-frequency and school-level beneficiary data, which is later collated and cross-tallied with the food grain and fund requests received through the BRPs.[7] On average, on a given day, 25 percent of the schools report that they do not provide meals conditional on answering the calls (see Figure A.1 generated from the IVRS data). Given that a large number of schools do not provide meals on a day and daily calls are not expensive, daily monitoring, as opposed to weekly or monthly calls, would be better at identifying legitimate issues and breakdowns and addressing them.[8]

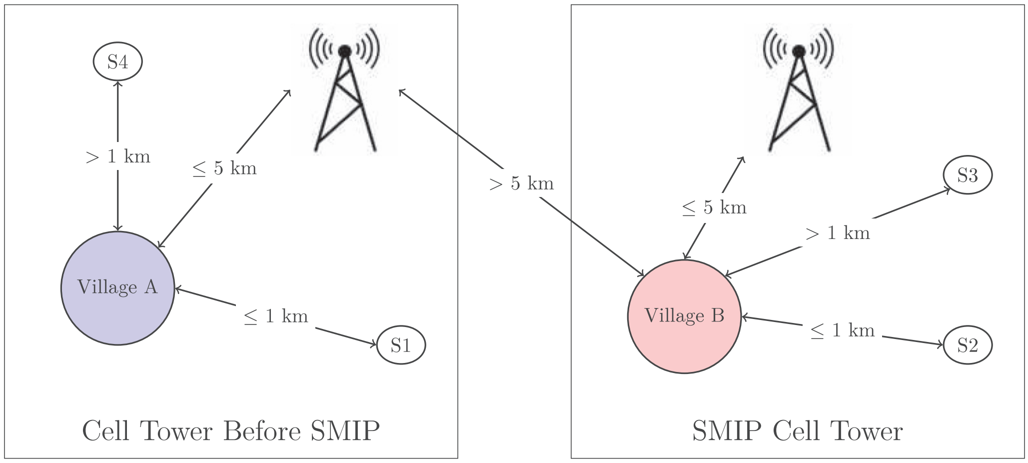
Under the IVRS, each school had to register five points of contact (mobile numbers), including one headmaster, two teachers, and two para-teachers. The system randomly calls any one of the five teachers in each school and collects data on the number of meals served at each school every day. If a school failed to serve any meals, the teacher is supposed to press zero 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, close to 70,000 schools in Bihar were

[5] Initially, the program provided 100 grams of take-home grains every day. In 2004, it transitioned from raw grains to cooked meals.

[6] Calculations are based on the exchange rate on 1st April 2015, 1 USD = 62.1697 INR.

[7] Chowdhary (2013) provides details of the program.

[8] Note that there is an annual target of meals to be served in a district based on historical enrollment. However, the allocation of cash and food grains happens monthly based on reports submitted by the BRP. IVRS data is not used for the allocations.



Village A getting cell coverage from an existing tower
Schools within 1Km of **Village A** (e.g. **S1**) dropped

Village B getting cell coverage from SMIP tower
Schools within 1Km of **Village B** are **Treated** (e.g. **S2**)
Schools >1 km from **Village A** and >1 Kms from **Village B** are controls (e.g. **S3** and **S4**)

Fig. 1. Illustrating the instrument.

required to serve meals to students. Mobile penetration density was not an impediment to the successful implementation of this reform.[9]

After completing the calls to all the schools, the IVRS summarizes the data and generates reports at the district, block, village, and school levels on attributes such as the number of attendees, meals served, adherence to the 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).

2.4. Monitoring and enforcement mechanisms

The institutional mechanism for monitoring rests with a four-tier Steering-cum-Monitoring Committee at the national, state, district, and block levels. The primary responsibility of these committees is to ensure that food grains and funds for cooking reach schools on time. School Management Committee, comprising parents and elected local leaders, are responsible for monitoring provision at a school level, but this does not happen effectively (Banerjee et al., 2010).

In addition, there are also three auditing levers used to maintain checks and balances. First, the Government of India has impaneled several monitoring institutes in districts responsible for assessing the progress and quality of the meals. These auditors are academicians who are contractually hired to make surprise visits to five percent of the total schools serving meals over two years in their district. Second, the BRP, a contractual government employee, is responsible for inspecting at least 30 schools every month. Third, monthly and quarterly progress reports submitted by the states to the central government are also used to assess the performance by the Ministry of Human Resources. Despite having a sound institutional framework, a survey by Aiyar et al. (2013) finds local-level monitoring weak. The status-quo enforcement was ineffective as there was no credible way to verify the monthly reports submitted by the headmasters.

2.5. Improvement in monitoring due to the IVRS

There are multiple reasons to believe that the introduction of the IVRS, which collects disaggregated high-frequency data directly from the schools, may reduce the leakages from the mid-day meal program.

First, the daily data obtained through the IVRS augments the field inspections as a monitoring tool that makes the end-line delivery more accountable and deters fraud. To this end, auditing agents are able to use the IVRS data to anchor their actions. Information provided by teachers on attendance and the number of beneficiaries for the day before an inspection serves as the baseline. If a deviation of more than ten percent between the field data and the IVRS data from the previous day is observed by the auditor, the headmasters are asked to explain the discrepancy. This can have a deterrence effect. The Directorate is able to use the information to assess large discrepancies in accounts. Should a discrepancy in the beneficiary details from the IVRS and the actual disbursement of grains and funds be detected, districts are asked to explain the reasons.[10] According to the Directorate of MDM

> “ … monitoring authorities now have actionable data that strengthens accountability. It has also resulted in an increased probability of fraud detection at the school level, as headmasters are held accountable every day. …

The Directorate has also been able to increase the number of inspections. The directorate highlights:

> … “*Dopahar* in conjunction with the MIS has impacted the inspection rates as well. The total inspection of schools in August 2012 was 12,544 and in January 2013 increased to 123,504. Out of these, action was taken against 2326 functionaries, and FIR was lodged against 54”. …

Second, since the IVRS randomly calls any one of the five registered phone numbers of the teachers to ascertain the meal details, embezzlement would require coordination among all the registered teachers

[9] 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.

[10] In June 2013, 31 out of 38 districts had less than 6% deviation between IVRS and the disbursement data (MIS). The Directorate of MDM issued show-cause notices to the rest of the seven district offices for an explanation.

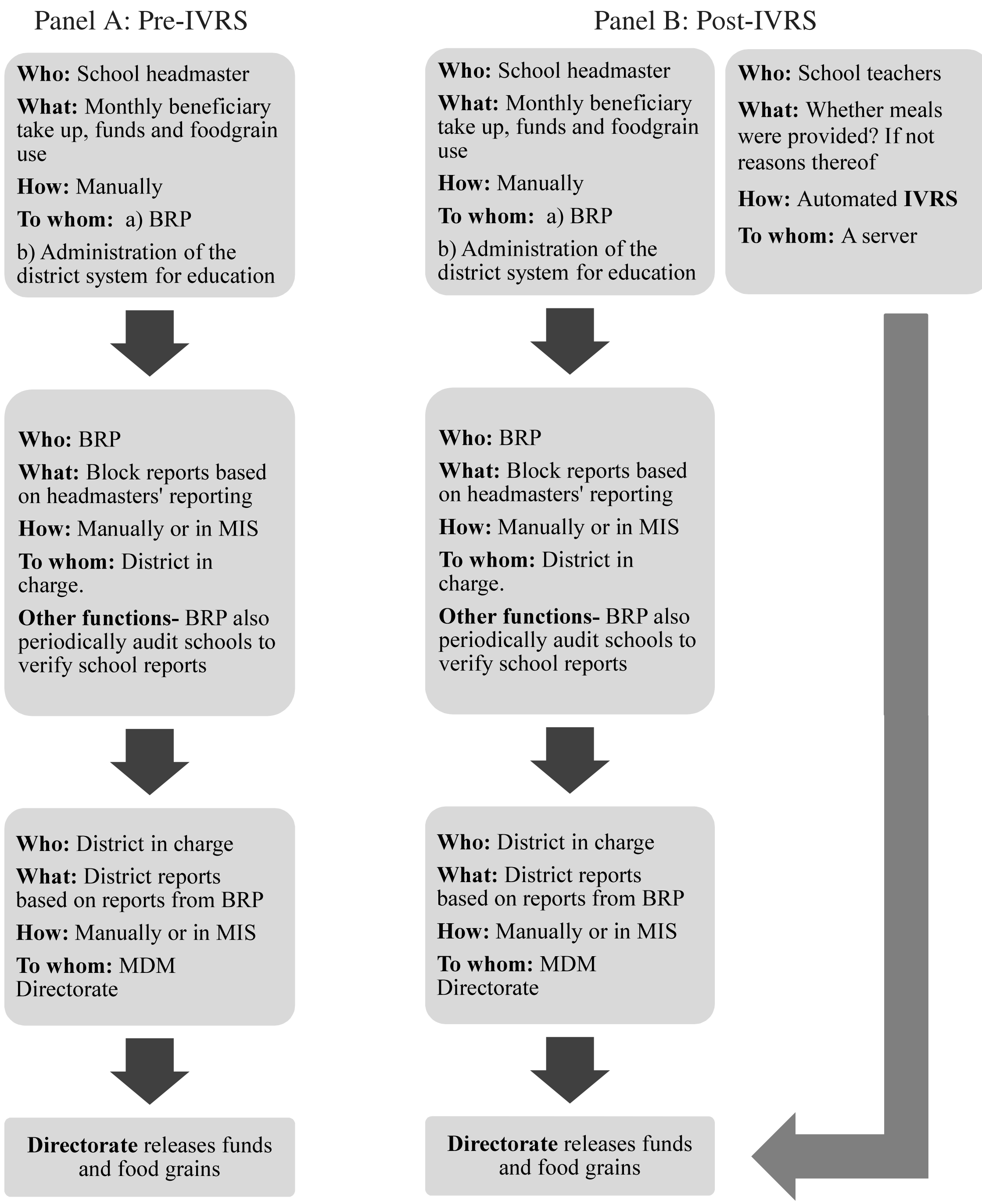


Fig. 2. Flow of beneficiary take up and other information pre- and post-IVRS.

and the auditing inspector. Therefore, the cost of colluding with and co-opting other teachers and the field inspector (auditors) increases. As calls are made daily, this could be a prohibitively high aggregate cost.

Finally, the information collected through the IVRS is made publicly available through a web interface. Citizens are also provided with a number to lodge grievances regarding the beneficiary numbers reported by the school teachers. This potentially increases the chances of detecting misappropriation.[11]

2.6. Strengthening of enforcement: Fines and consequences

Upon auditing, a discrepancy of more than ten percent between the field data and the IVRS-reported numbers is considered misreporting of information by the school teachers. The Directorate assumes misappropriation of funds by the relevant officiating teacher, and a fine is imposed as follows: the discrepancy between the field and the IVRS data multiplied by the number of working days in the last three months multiplied by the cost of providing a meal. Anecdotal evidence suggests that this was a binding constraint. For example, a newspaper article highlights irregularities at the time of the annual assessment of schools in the district of *Araria*. Around 36% of the beneficiaries were ghost consumers of the meals served by the schools, and in fact, these fake students had never attended school. Following the incident,

[11] Literacy and internet penetration rates are low in Bihar, and hence this is less likely to be a prominent reason.

251 of the 2080 school headmasters were fined between Rs. 20,000, and Rs. 100,000; equivalent to 50%–260% of the monthly salary of a headmaster of a secondary school.[12]

3. Conceptual framework

The State MDM department delegates the task of serving lunch at schools to district and sub-district level administrative staff and school teachers with very little oversight. This hierarchical setting resembles a standard principal–agent problem. There are two agents *Block Level Officers* and *Headmaster* who sequentially handle requests for funds and grains and then deliver these to the intended beneficiaries.

The *Headmaster* sends a request to the *Block Level Officers*, who then forwards it to the directorate. The *Block Level Officers* has to verify requests and ensure food grains and funds reach the schools. The cost of monitoring every school every day is very high for the directorate. The directorate conducts random field inspections with some frequency of a certain percentage of schools in each inspection round. Other than this, there is no other way to verify the records that the *Block Level Officers* maintains or requests he forwards. There is a black market for grains.

Status quo. The two agents expect a probability of detection. Given the periodic nature of field inspections, this probability is low. Therefore, the agents co-opt and embezzle from the delivery chain. There are two ways in which this can be done. One, they can rig the number of beneficiaries and state more beneficiaries than there are students enrolled in schools. Since grain and funds to convert it into food are based on the number of beneficiaries served, the agents get to fleece this off the system the grain and funds provided for these *ghost beneficiaries*. Two, the *Headmaster* can also not serve all the intended beneficiaries (they can serve few or not at all). In this case, too, the food grain received can be sold in the black market, and the funds to convert grain into food be embezzled.

Under IVRS system. The directorate introduces a new low-cost technology that makes the coordination between agents expensive. This technology calls randomly chosen teachers, including the headmaster, from among the pre-identified set of five teachers from the school every day. The system automatically calls and records the service of meals and beneficiaries served. Now, the *Headmaster* and the *Block Level Officers* find it costly to coordinate daily about what to say. Also, the call is made to other teachers as well, so they have to co-opt them too. This raises the probability of detection. Hence, leakage from the system falls.

3.1. Hypothesis

Based on this, we would predict the following:

- Number of Beneficiaries would fall.
- If schools are under-serving the student beneficiaries before, then in independent assessment, meal provision and cooking should increase
- School enrollment numbers reported to the system should fall
- As students are likely to get the meal, attendance should increase

There are two alternative scenarios. One, there is no leakage before, and IVRS only improves the efficiency and time it takes to get the grain and funds. If this were the case, the number of beneficiaries and enrollment would not fall. We can empirically test this scenario. The other is that the *Block Level Officers* are shirking and *Headmaster* cheats. If this is the case, the *Block Level Officers* would report to the directorate whatever he is told without verifying and rely completely on what *Headmaster* tells him. We cannot rule this out empirically. However, given that there were field inspections with some periodicity and in a year all schools were covered, it is not very likely that the cheating of the *Headmaster* would never come to light and the *Block Level Officers* would not discover it.

4. Data

We use four main sources and two ancillary sources of data for carrying out our analysis.

4.1. Independent data: ASER

The independent assessment is based on the Annual Status of Education Report (ASER) surveys carried out by the NGO *Pratham* over the period 2009–2014.[13] ASER primarily covers the 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. Our sample comprises the data from five states in India that are socio-economically similar to Bihar and geographically proximate. These include Bihar, Chhattisgarh, Jharkhand, Orissa, and Madhya Pradesh.[14] The estimation sample is a representative repeated cross-section at the school- and household-level.

For each village, one government school (if any) is surveyed randomly. The survey collects information on two vital variables: headmaster's or teachers' response on whether meals have been served on the date of the interview and whether the interviewer observes if a meal is being cooked in the school. 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 teachers present on the day of the interview. In addition, ASER surveys record the grade-wise enrollment and attendance data for first through eighth grade. We restrict our analysis to enrollment and attendance only to primary grades (grades one through five).[15] The sample includes 6392 schools in Bihar and 25,329 schools across all five states.

Panel A in Appendix Table A.2 reports the summary statistics for the ASER data. Out of the 6105 schools surveyed in Bihar, about 65 percent reported serving meals, whereas in the full sample, 84 percent of the schools reported affirmatively. According to the ASER enumerator observation-based measure, 58 percent schools in Bihar served meals, while the number was higher at 73 percent for the full sample. In the remaining paper, we will refer to the ASER data as *Independent data*.

4.2. Official records: AWPB

Our official statistics data comes from government records. We use district-level Annual Work Plan Budgets (AWPB) 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 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, and beneficiaries. These data are available for both primary

[12] Source: https://tinyurl.com/htmdmghost.

[13] These surveys are available from 2005 onwards, 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.

[14] 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 and one year of limited pre-data. As a result, we are not able to include it in our sample.

[15] We do not include upper-primary grades as many schools do not have classes beyond the fifth grade.

and upper primary schools at the district level. Our Bihar data has 38 districts and 228 district-year observations, and 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.

Panel B in Appendix Table A.2 describes the summary statistics of the AWPB data. According to the official records, about 99 percent of primary and upper primary schools serve meals. While the percentage of beneficiaries availing meals (out of total enrollment) stand at 91 and 88 percent, respectively, in Bihar, the numbers reported in column (5) are slightly smaller for the full sample. We will refer to this data as the *Official Data*.

4.3. Digitally recorded data: IVRS

The third dataset comes from the technology-enabled platform. The IVRS calls the schools in Bihar every day and collects information on whether the school provided the meal, the number of beneficiaries and attendees, and the main reason thereof if the school did not provide the meal. This data is digitally recorded for 74,255 schools every working day between 04/08/2012 and 12/30/2017. Our data comprises of 95.97 million school-day observations.

4.4. Administrative records: DISE

Finally, we also use school-level administrative data from the District Information System for Education (DISE) reports for our five sample states. DISE is published annually by the National University of Education Planning and Administration (NUEPA). Each year the report roughly covers 662 districts, 1.4 million schools, 199.71 million students, and 7.35 million teachers. This data is used for controlling school characteristics in many of our specifications. We also use this data for the period 2012 to 2014 to cross-tally the school enrollment reported by the headmasters to the IVRS and the DISE authorities.

4.5. Central government audit reports: Independent monitoring institutes

To explore the sufficiency and quality of meals, we use audit reports published by independent monitoring institutes.[16] 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 five 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.[17] We have 180 district-year observations in this sample.

Our ancillary sources include the Census of India, 2011, and the digital elevation model of India. District characteristics across Bihar and other states reveal differences across some margins and similarities on other. The summary statistics are reported in Appendix Table A.3. More villages in Bihar have post offices, but fewer have electricity. These level differences will not be a source of bias in our estimation.

5. Estimation

We motivate the analysis by documenting a comparison of outcomes in Bihar before and after the reform. The empirical model we estimate is as follows:

$$y_{dt} = \alpha_0 + \sum_{t=2009}^{2014} \alpha_t \times \tau_t + \alpha_X X_{dt} + \delta_d + \epsilon_{dt}, \tag{1}$$

where y_{dt} is the outcome variable measuring provision of meals in district d in year t. τ_t represents dummy variable for year t. The year 2009 is the reference year. X_{dt} is a vector of school characteristics at the district-year level.[18] The specification also includes district fixed effects (δ_d). The parameters of interest are α_ts. While this analysis ascertains whether the timing of changes in outcomes aligns with the timing of the reform, it does not account for the secular trends over time.

To address this and establish causality, we take three approaches to identification approaches:

5.1. Difference-in-differences approach

Our first approach involves estimating a difference-in-difference model. We compare the effects of the IVRS on meal provision across the districts of Bihar and the rest of the states before and after the reform.[19] The empirical model is as follows:

$$y_{dt} = \beta_0 + \sum_{t=2009}^{2014} \beta_t \times \text{Bihar} \times \tau_t + \beta_X X_{dt} + \tau_t + \delta_d + \epsilon_{dt}, \tag{2}$$

while other control variables remain the same as in the previous specification; here we interact the year indicators with an indicator *Bihar*, which takes the value one for the state of Bihar and zeros for the other states. Thus, the parameters of interest, β_ts, are the treatment on treated DID estimates which show the effect of IVRS on outcomes in districts of Bihar in year t. Under our identifying assumption of parallel pre-trends, any secular trends in outcomes are accounted for. To bolster our identification, we also augment this specification in many ways. We show that our estimates are robust to controlling for district-specific trends and estimating a generalized DID model.

5.2. Synthetic difference-in-differences approach

Our Second approach is using a synthetic difference-in-differences estimation strategy. Since one state is treated in our setting, we construct a synthetic counterfactual or control for our treated state to address the selection on unobservables. We use the novel "Synthetic Difference in Differences" method proposed by Arkhangelsky et al. (2021). Intuitively, this combines insights from the difference in differences (DID) and synthetic control (SC) methods (Abadie et al., 2010, 2015).

The weights $\hat{\lambda}_t^{sdid}$ and $\hat{\omega}_i^{SDID}$ in Eq. (3) are used in the basic two-way fixed effects regression to estimate the average causal effect of treatment (τ):

$$(\hat{\tau}^{SDID}, \hat{\mu}, \hat{\alpha}, \hat{\beta}) = \underset{\alpha,\beta,\mu,\tau}{\arg\min} \left\{ \sum_{i=1}^{N} \sum_{t=1}^{T} (Y_{it} - \mu - \alpha_i - \beta_t - B_{it}\tau)^2 \; \hat{\omega}_i^{SDID} \; \hat{\lambda}_t^{SDID} \right\} \tag{3}$$

In other words, it emphasizes units that are on average similar in terms of their past to the treated units and periods that are on average similar to the treated periods or post periods.[20]

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

[17] 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 the 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.

[18] School level characteristics include the fraction of schools with separate girls' toilet, drinking water, and playgrounds; the number of head teachers, total appointed teachers.

[19] Districts are the administrative unit under the state. Our control states are close to Bihar and have a comparable socio-economic profile.

[20] While SC methods eliminate pre-trends, SDID makes them parallel. Arkhangelsky et al. (2021) provide detailed insights and statistical properties of this method.

This has two benefits. The time weights can remove bias by eliminating the role of time periods that are very different from the post periods. Unit weights accomplish this by focusing on similar units. This can also improve precision if there is heterogeneity in outcomes by units or times by removing this systematic part.[21] Including unit fixed effects makes the model more flexible, increasing its robustness. The unit fixed effects also absorb much of the variation in outcomes and can improve precision. The synthetic counterfactual, by construction, has parallel trends prior to treatment in the outcome variables.

5.3. Instrumental variable approach

In our third approach, we make use of the variation within the state of Bihar across districts in IVRS call completion rates in an instrumental setting. A possible concern with identification is that the state of Bihar was cracking down on corruption and the findings are a result of that government's stance. By harnessing the variability of the call completion data within *Bihar*, we cast doubt on the possibility that the results were a result of a general crackdown on corruption.

There is variation within Bihar in IVRS call completion, and outcomes such as attendance and meal provision are positively correlated with both the number of calls completed and call intensity (percentage of calls completed among total calls made on working days in a month). We leverage a government of India telecommunication initiative that increased cell phone coverage in rural India in an instrumental variable framework to establish causal effects of IVRS call completion on meals provided and attendance. If our results were driven by other Bihar-specific interventions, within Bihar exogeneous variation in IVRS completion would not influence these desirable outcomes, viz., attendance and meal provision.

5.3.1. Shared mobile infrastructure program

The Indian government decided to expand telecommunication coverage in areas where market demand did not attract private investment. In 2003, the government set up The Universal Service Obligation Fund (USOF) to provide affordable telecommunication to unconnected villages. At the time, 41% villages of India were uncovered, and the intent was to cover these villages. Bids were invited from public and private infrastructure providers to construct mobile towers under the 'Shared Mobile Infrastructure Program' (SMIP). The government provided subsidies for the construction and maintenance of mobile towers.

In Phase-I of the program, 7353 mobile towers were installed in villages that did not have fixed wireless or mobile coverage. These towers were built between 2007 and 2010 and are spread over 500 districts and 27 states in India. Besides remoteness and lack of mobile coverage, these villages were chosen from about 300,000 unconnected villages in India on the basis of their population. Villages with a population greater than 2000 were prioritized in Phase-1 of the program. The infrastructure providers (IPs) were responsible for setting up, operating, and maintaining these sites for a period of six and a half years.[22]

Coverage under shared mobile infrastructure program (SMIP):. Universal Service Obligation Fund (USOF) identified the set of villages to be considered for mobile connectivity under the SMIP based on the 2006 wireless coverage report prepared by The Wireless Planning & Coordination (WPC) wing of the Department of Telecommunications (DoT). We obtained this report. There were 236,240 uncovered villages as of 2006.

Tower locations and covered villages:. To determine the location of the towers, the USOF manually created village clusters using WPC coverage data and boundary maps from the Survey of India to maximize the covered population. Within each cluster, preliminary tower locations were then determined manually. The coverage radius of each tower was assumed to be about five km.[23] Subsequently, tower locations were optimized using digital elevation maps and radiofrequency analysis.[24] Based on this process, the USOF prepared a list of 7871 unique locations to construct mobile towers covering 256,234 villages.[25] Of these, only 7393 towers were actually built. 4849 towers were built on the original proposed location, but 2544 were relocated due to inadequate electricity supply or topographical limitations. Gupta et al. (2020) study the effect of this program on agricultural technology adoption and productivity, and Bubna and Debnath (2017) examine the effects of mobile coverage on inequality using this program as a source of variation. We ascertained the villages covered by these towers in the state of Bihar. An important point to note is that the SMIP towers were all built before the IVRS program commenced. Hence, unlike the above-mentioned papers, we do not use program roll-out as our source of variation.

To obtain a plausibly exogenous instrument that affects the call completion rate of schools, we leverage the SMIP tower's location. Fig. 3 shows towers added under SMIP in Bihar. We obtained the geo-coordinates (latitude and longitude) of the schools in our sample, the cell towers, and all villages in Bihar to construct the instrument. These three are point data. We do not have polygons for villages and hence cannot place schools within villages. With that caveat, we constructed the instrument as follows.

Construction of the instrument:. We divided the villages with mobile coverage into two groups: villages in group A had mobile coverage before SMIP, whereas villages in group B received mobile coverage only under SMIP which did not respond to local conditions such as demand for mobile telephony.[26] We then created two distance matrices — one populated by the distances from each school to each village in group A and the other containing the distances from each school to each village in group B.[27] Having created the distance matrices, we computed the distance of each school from the nearest village in each group.

To compute our instrument based on the distance measures described above, we use the distance of schools from group B villages, where the towers were constructed under the SMIP, and from group A villages, which already had mobile connectivity through private providers. In this analysis, we drop all schools located in villages in group A from our sample — these are schools within one km from any village in group A. In the resulting sample, we define '*coverage*' as an indicator taking the value one for a school within one km from a group B village but more than one km away from any Group A village. It takes value zero if schools are more than one km away from villages in

[21] The precision can worsen relative to DID if there is little heterogeneity by units or time periods.

[22] The IP was responsible for the land, tower, electrical connection, power backup, boundary wall, and security cabin.

[23] The coverage radius varied between the plains and hilly terrains.

[24] This information is based on numerous conversations with individuals closely associated with the project at the Centre for Development of Telematics, DoT.

[25] The number of villages in this proposed list exceeds the number of uncovered villages in the 2006 WPC report. This is because of the overlap in the villages covered by multiple towers. Additionally, some of the villages with existing mobile coverage fell within the proposed tower's coverage area.

[26] We use a buffer of 5 km around cell towers to determine whether a village has mobile coverage; a village is covered only if it falls within the buffer zone of at least one cell tower constructed under SMIP. As discussed before, this 5 km radius was chosen on the basis of expert opinion regarding the range of cell towers in India.

[27] These distances were calculated using Vincenty's formula (Vincenty, 1975) for the geographic distance between points on the Earth, which is based on the assumption that the Earth is an oblate spheroid, making the calculated distances significantly more accurate than other methods.

Fig. 3. SMIP tower locations in Bihar.
Notes: Graph constructed using GIS data for the mobile towers constructed under SMIP, based on data from the Universal Service Obligation Fund (USOF). The tower locations, marked using black circles, are superimposed on a district-level map of Bihar.

either group so that they are less likely to have reliable cell coverage. We use '*coverage*' as an instrument for call completion/intensity. Fig. 1 illustrates the construction of this instrument. In the left panel village A belongs to group A and it has mobile connectivity from an existing tower. School $s1$ is within one km. from this village and therefore is dropped from the analysis while school $s4$ is more than one km. away and is retained in the estimation sample. School $s4$ is also more than one km. away from village B which received mobile connectivity under SMIP. School $s3$ in the right panel is also more than one km. away from both the villages. Therefore, it is unlikely that these two schools will have reliable connection and the variable *coverage* takes the value zero for them. School $s2$ however is within one km. from village B, but more than one km. away from village A. The variable *coverage* takes the value one for school $s2$ as it is more likely to have mobile connectivity from a tower built under SMIP.[28]

We leverage the coverage due to the SMIP towers as an instrument to appraise the effects of call completion under the IVRS. The intuitive idea is that the headmasters in schools closer to the coverage area of these towers but were far away from pre-existing towers would have better mobile connectivity and be able to complete the IVRS calls with ease. Since the tower location was not based on MDM program success or local demand, this is arguably an exogenous source of variation (conditional on village population, ruggedness, and elevation) in call completion rate. We utilize the school-level monthly data on attendance, meals served, and the number of completed calls between April 2012 and November 2014 from the IVRS system to test how these were affected by call completion rate. We then estimate an instrumental variable model as follows:

The first stage is given by the following

$$\begin{aligned} C_{smd} = {} & \alpha_0 + \alpha_1\, Coverage_{sd} + \alpha_2\, Village\ population \\ & + \alpha_3\, Village\ Ruggedness \\ & + \alpha_4\, Village\ elevation + \delta_d + \mu_m + \tau_{dm} + \epsilon_{smd} \end{aligned} \tag{4}$$

where C_{smd} is the number of calls completed or call intensity depending on the specification in school s, month m, and district d. $Coverage_{sd}$ is the indicator for the distance metric of the school from the nearest coverage area of a SMIP tower, as explained above. δ_d is the district fixed effect, μ_m is the month fixed effect, $\tau_d m$ is the district-specific time trend. We control for the population of the village as the population was the basis for prioritizing the SMIP towers' placement. Ruggedness and elevation affected the location of the towers. To the extent population, ruggedness, and elevation may also affect the provision of MDM meals at schools, conditioning on these leads to satisfaction of the exclusion restriction for the instrument.

The second stage is as follows:

$$\begin{aligned} Y_{smd} = {} & \beta_0 + \beta_1\, \hat{C}_{smd} + \beta_2\, Village\ population + \beta_3\, Village\ Ruggedness \\ & + \beta_4\, Village\ elevation + \delta_d + \mu_m + \tau_d m + \nu_{smd} \end{aligned} \tag{5}$$

where Y_{smd} are outcomes such as average daily attendance and average daily attendance normalized by enrollment and $\hat{C}_{smd}$ is the predicted value of the number of calls completed (or call intensity) in school s in month m in district d. Standard errors are clustered at the level of the bl. As a sensitivity check, we also show results clustered by school.

Concerns about exclusion restrictions. There are two concerns with the validity of our instruments. The first concern is that the towers could have affected other outcomes as illustrated by Gupta et al. (2020), Bubna and Debnath (2017) which could confound the results. However, the SMIP towers were already constructed before the IVRS was introduced. The other papers (Gupta et al., 2020; Bubna and Debnath, 2017) show that district-level outcomes change because of the roll-out of the SMIP towers, which happened much before the reform we are studying. Hence, the effects of the SMIP towers on outcomes are present at the baseline of the IVRS rollout. If these district-wide effects are time variant, our IV estimation includes district-fixed effects and absorbs these. Moreover, we are also controlling for district-specific trends. This subsumes any time-varying effects of the SMIP towers at the district level, which were already underway by the time IVRS was rolled out. Cell towers can improve price dispersion and productivity; however, it is unlikely that these changes would matter for schools within one km of villages that are covered by the towers but not schools that are more than one km away, which is what our instrument harnesses.

The other concern is that the SMIP towers improved the monitoring of other state programs locally, which led to the improvement of MDM provision in schools, i.e., the instrument is correlated with the error in

[28] See Table A.4 for the summary statistics of schools by coverage status.

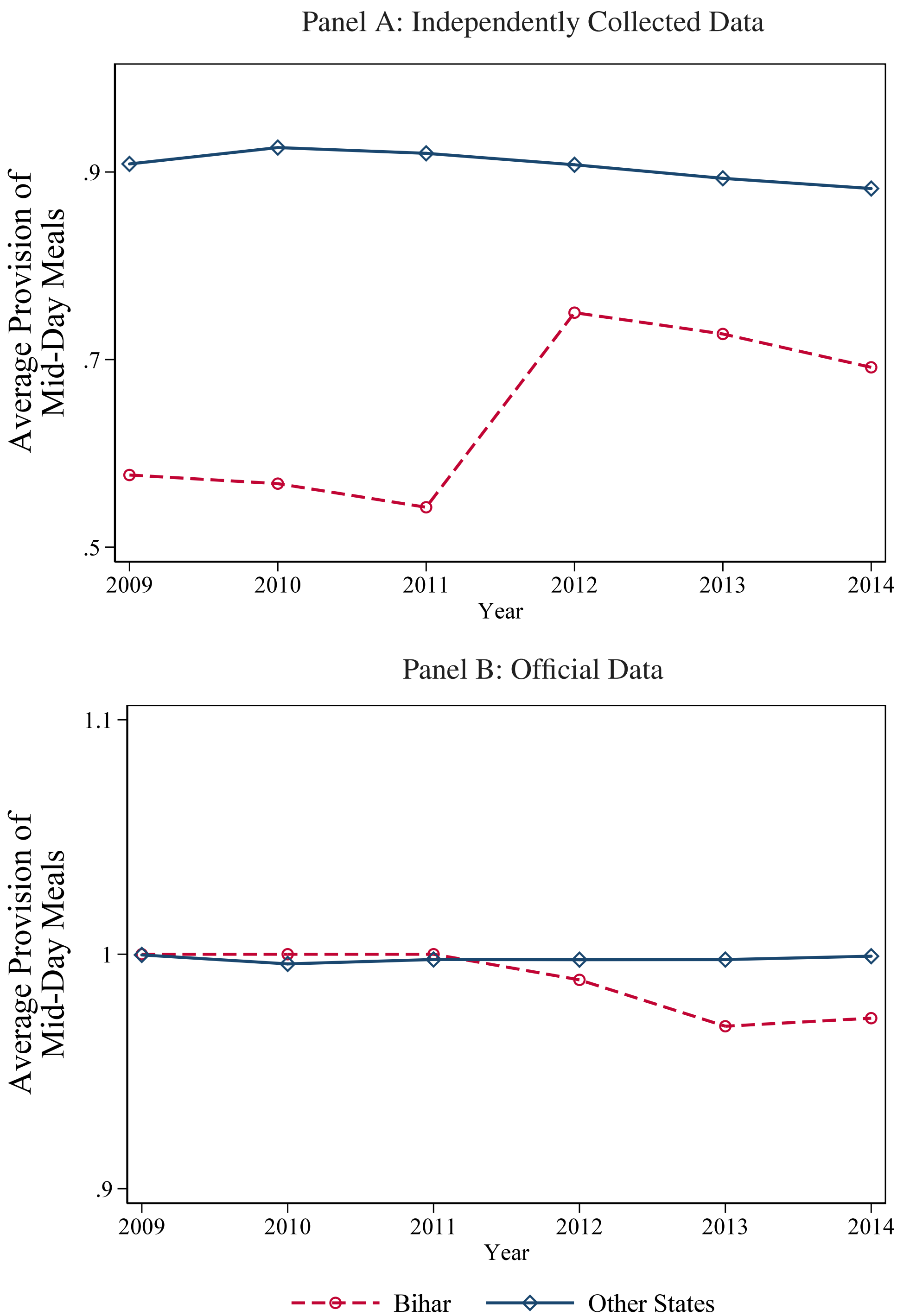


Fig. 4. Fraction of schools serving mid-day meals.
Note: Independently collected school (primary and upper primary) level data are from the Annual Status of Education Reports (ASER). District level Annual Work Plan Budgets (AWPB) for primary and upper primary schools submitted to the Government of India by the state mid-day meal authorities constitute the source for official data. Other states include Jharkhand, Madhya Pradesh, Orissa and Chhattisgarh.

our estimation. The SMIP mobile towers would have to improve the monitoring of other state programs in a way that the MDM provision improves in close by schools (within 1 KM) but not at distances greater than one km. While this is conceivable, it is less likely. We also rerun our IV specification using pre-post differences as outcomes instead of levels. If there are effects of monitoring due to SMIP towers on MDM provision, they will be captured in the baseline values of MDM provision. The difference will net them out and give us the results on changes accruing due to IVRS introduction in 2012.

6. Results

6.1. Main results from the difference-in-differences estimation

Our main analysis focuses on assessing the impact of the IVRS on curbing leakages. To this end, we ascertain any discrepancies in the assessment of beneficiary take-up based on the state's official and independently collected data. The main finding of our analysis is borne out visually in Fig. 4, where we plot the raw data averages from the

Table 1
Effect of IVRS on mid-day meal provision using independent data.
(Bihar, Pre-Post Analysis.)

Dependent variable	School provides meal		MDM cooked on the day of visit	
Baseline average	56.203	56.203	50.309	50.309
	(1)	(2)	(3)	(4)
Two years before IVRS	−0.32	−0.84	5.09	4.63
	(3.51)	(3.68)	(3.70)	(3.83)
	[−7.364, 6.366]	[−8.067, 6.583]	[−2.169, 12.74]	[−2.888, 11.96]
One year before IVRS	−4.07	−5.89	2.20	0.48
	(3.86)	(3.92)	(3.85)	(3.95)
	[−12.08, 3.902]	[−14.25, 2.393]	[−5.632, 9.999]	[−7.166, 8.372]
IVRS year	16.5***	14.0***	17.7***	15.3***
	(3.50)	(3.55)	(4.10)	(4.07)
	[9.211, 23.84]	[6.617, 21.6]	[9.249, 25.81]	[7.385, 23.34]
One year after IVRS	13.7***	10.5**	13.7***	10.6**
	(4.36)	(4.37)	(4.60)	(4.51)
	[5.145, 22.82]	[1.831, 19.37]	[3.909, 22.93]	[1.764, 19.49]
Two years after IVRS	10.6**	7.54*	14.8***	11.8***
	(4.28)	(4.22)	(4.48)	(4.32)
	[2.162, 19.74]	[−1.173, 16.29]	[5.503, 24.15]	[3.011, 20.71]
Post IVRS–Pre IVRS	17.77***	16.37***	11.5**	10.12**
School characteristics	No	Yes	No	Yes
F-stat for joint significance of pre-coefficients	0.55	1.13	1.00	0.74
R squared	0.062	0.069	0.074	0.081
No. of observations	4828	4828	4828	4828

Notes: We use independently collected school-level data for the years 2009–2014. The sample is restricted to schools in the state of Bihar. The dependent variable, school provides meal takes the value one if the headmaster reported providing a meal to the survey team on the date of the survey and zero otherwise. The other dependent variable, MDM cooked takes the value one if the meal was cooked in the school on the date of the survey and zero otherwise. 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. Post IVRS–Pre IVRS reports the difference in the coefficients on One year after IVRS and One year before IVRS. ***, **, and * indicate significance at the levels of 1%, 5%, and 10%, respectively. Robust standard errors clustered at the district level are reported in parentheses. 95% confidence intervals for the coefficients of interest from a wild cluster bootstrap analysis using district-level clustering are presented in square brackets.

Independent data (Panel A) and the *official data* (Panel B). The solid line represents the yearly average outcome variable for other states, and the dashed lines represent the same for the state of Bihar. In Panels A and B, we observe similar trends for Bihar and other states until 2011, albeit the levels are different in Panel A. What stands out is the divergence in the opposite direction for Bihar in independent and official data after the reform kicks in. In Panel A, the average provision of mid-day meals from the *Independent data* improves significantly for Bihar while the other states show no change. In stark contrast, in Panel B, using *official data*, we find a decline in the average provision in Bihar relative to other states. We take this as prima facie evidence that the reform was successful at curbing leakages.

Another striking pattern observed in the data helps us to comment on the nature of leakages. Post-reform, data was collected by the MDM directorate from two sources: the schools using the IVRS and the official status quo channel (Quarterly Progress Reports or QPRs) informed by the BRPs. In Fig. 5, we compare the distribution of beneficiaries obtained from these two sources for the period April 2012–November 2014. In addition, we also plot the distribution of enrollment from the QPR for the same period. Two facts stand out: first, BRP reports beneficiaries approximately equal to enrollment; and second, there is a stark divergence between beneficiaries reported by the BRP as official statistics and those reported by the school to the IVRS. In Fig. 6, we show that the enrollment distributions as per these sources are similar, implying that the BRPs are taking the enrollment figures provided by schools at face value and just reporting those as beneficiaries. Hence, in our assessment, the distribution channel does not cross-check the statistics reported by schools and thus induces inefficiencies in the system, which remain even after the reform. This is not likely to be the source of leakage though we cannot rule out that these agents are co-opted, so they do not exert any effort. In contrast, post the reforms, the last-mile delivery is affected and the schools resort to reporting accurate beneficiary statistics and update their reporting. This suggests that the

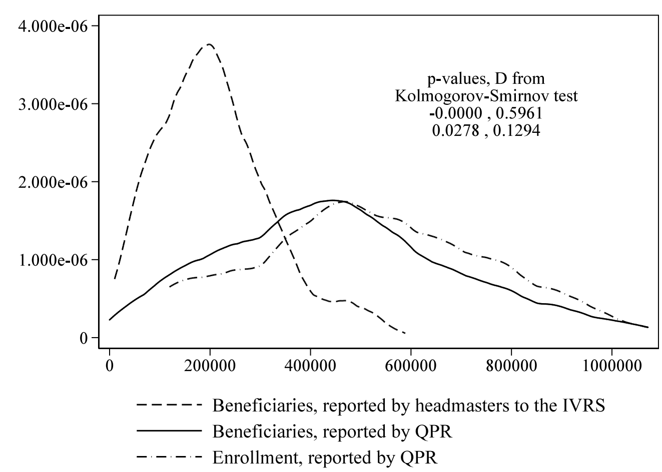


Fig. 5. Distribution of beneficiaries reported by headmasters to the ivrs and quarterly progress reports submitted by the state.
Notes: We use district-level quarterly data on enrollment from the IVRS data and the quarterly progress reports for the state of Bihar between April 2012 and November 2014.

leakage was happening at this echelon of the delivery chain. Below we describe and discuss the results of our statistical analysis related to these changes in detail.

6.1.1. Independent data based estimates

We report the results from our estimation of Eq. (1) in Table 1. In columns 1 and 2, the outcome variable is whether a school provides meals or not, as reported by the teacher to the survey team that collected the independent data. In the pre-reform 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

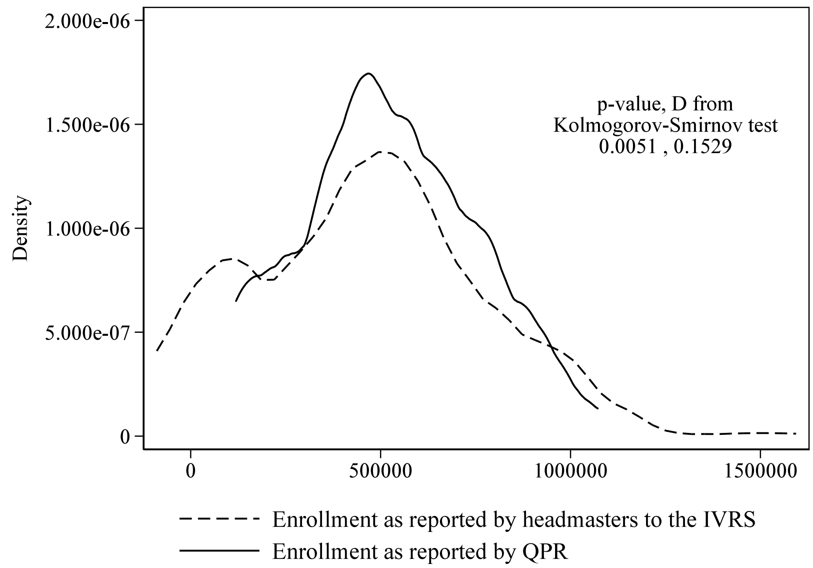


Fig. 6. Distribution of enrolled students reported by headmasters to the IVRS and quarterly progress reports submitted by the state.
Notes: We use district-level quarterly data on enrollment from the IVRS data and the quarterly progress reports for the state of Bihar between April 2012 and November 2014.

Table 2
DID estimate of IVRS on mid-day meal provision using independent data.

Dependent Var.	School provides meal		MDM cooked on the day of visit	
Baseline average	56.203	56.203	50.309	50.309
	(1)	(2)	(3)	(4)
Bihar × 2010	−2.15	−3.13	−4.45	−6.13
	(3.68)	(3.75)	(4.10)	(4.16)
	[−9.338, 5.221]	[−10.04, 3.979]	[−12.81, 3.998]	[−14.52, 2.062]
Bihar × 2011	−5.00	−6.57	−5.67	−8.27*
	(3.99)	(4.00)	(4.23)	(4.24)
	[−13.06, 2.969]	[−14.63, 1.552]	[−13.93, 2.538]	[−17.03, .1314]
Bihar × 2012	17.6***	16.0***	19.4***	16.8***
	(3.70)	(3.70)	(4.57)	(4.50)
	[10.33, 25.37]	[7.963, 23.51]	[9.884, 28.36]	[7.527, 26.17]
Bihar × 2013	15.8***	13.7***	17.7***	14.1***
	(4.53)	(4.50)	(4.98)	(4.94)
	[6.592, 25.43]	[4.452, 22.9]	[8.187, 27.51]	[4.013, 24.13]
Bihar × 2014	13.6***	11.6**	18.8***	15.5***
	(4.55)	(4.51)	(4.99)	(4.92)
	[4.557, 22.37]	[2.568, 20.49]	[8.567, 28.67]	[5.228, 25.85]
Post IVRS–Pre IVRS	20.85***	20.26***	23.33***	22.41**
School characteristics	No	Yes	No	Yes
F-stat for joint significance of pre-coefficients	0.88	1.52	1.16	2.31
R squared	0.144	0.148	0.109	0.114
No. of observations	18667	18667	18667	18667

Notes: We use independently collected school-level data for the years 2009–2014. The sample is restricted to schools in the states of Bihar, Chhattisgarh, Jharkhand, Madhya Pradesh, and Orissa. The dependent variable, school provides meal takes the value one if the headmaster reported providing a meal to the survey team on the date of the survey and zero otherwise. The other dependent variable, MDM cooked takes the value one if the meal was cooked in the school on the date of the survey and zero otherwise. 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. Post IVRS–Pre IVRS reports the difference in the coefficients on One year after IVRS and One year before IVRS. ***, **, and * indicate significance at the levels of 1%, 5%, and 10%, respectively. Robust standard errors clustered at the district level are reported in parentheses. 95% confidence intervals for the coefficients of interest from a wild cluster bootstrap analysis using district-level clustering are presented in square brackets.

effect is statistically significant at the one percent level and persists in the first post-reform year 2013. The pre-post comparison indicates an improvement of 18 percentage points. On a baseline average of 56.2, this is a 32 percent increase. This is robust to the inclusion of school-level controls reported in column 2.[29] In analogous specifications for whether the enumerator observed meal provision or not, we find a similar pattern as reported in columns 3 and 4. Comparison of pre-post coefficients indicates an improvement of 11.5 percentage points, which is a 23 percent increase over a base of 50.3.

The DID estimates from specification (2) are reported in Table 2. Our DID estimates are remarkably similar to the estimates reported in Table 1. For the first outcome, the estimates in column 1 indicate interaction coefficients are small and insignificant prior to 2012, then it jumps and exhibits a large positive and statistically significant (17

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

Table 3
Effect of IVRS on mid-day meal provision using official data.
(Bihar, Pre-Post Analysis.)

Dependent variable	Percentage of schools serving MDM		Percentage of beneficiaries availing MDM	
	Primary	Upper primary	Primary	Upper primary
Baseline average	100	100	100	100
	(1)	(2)	(3)	(4)
Two years before IVRS	−0.00	−0.00	−0.00	−0.00
	(0.25)	(0.23)	(0.31)	(0.57)
One year before IVRS	−0.00	−0.00	−0.00	0.00
	(0.25)	(0.23)	(0.31)	(0.57)
IVRS year	−1.01**	−1.24**	−4.91***	−6.74***
	(0.50)	(0.59)	(0.31)	(1.83)
One year after IVRS	−1.37***	−5.33***	−34.08***	−36.73***
	(0.43)	(0.34)	(1.01)	(1.19)
Two years after IVRS	−3.55***	−1.64***	−14.97***	−24.81***
	(0.42)	(0.32)	(0.55)	(0.57)
Post IVRS–Pre IVRS	−1.37***	−5.33***	−34.08***	−36.73***
F-stat for joint significance of pre-coefficients	0.00	0.00	0.00	0.00
R squared	0.451	0.600	0.956	0.890
No. of observations	228	228	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. Post IVRS–Pre IVRS reports the difference in the coefficients on One year after IVRS and One year before IVRS. ***, **, and * indicate significance at the levels of 1%, 5%, and 10%, respectively. Robust standard errors clustered at the district level are reported in parentheses.

Table 4
DID estimate of IVRS on mid-day meal provision using official data.

Dependent variable	Percentage of schools serving MDM		Percentage of beneficiaries availing MDM	
	Primary	Upper primary	Primary	Upper primary
Baseline average	100	100	100	100
	(1)	(2)	(3)	(4)
Bihar × 2010	0.49**	0.16*	2.77	4.56
	(0.21)	(0.09)	(7.39)	(4.83)
Bihar × 2011	0.18*	0.15*	−3.15	5.37
	(0.09)	(0.09)	(5.30)	(3.70)
Bihar × 2012	−0.67	−1.03	−9.50	−20.4***
	(0.54)	(0.71)	(6.56)	(4.88)
Bihar × 2013	−1.07**	−5.08***	−41.6***	−47.6***
	(0.52)	(0.40)	(4.26)	(3.34)
Bihar × 2014	−3.43***	−1.60***	−29.2***	−37.6***
	(0.51)	(0.33)	(1.92)	(2.48)
Post IVRS–Pre IVRS	−1.25**	−5.22***	−38.41***	−52.94***
F-stat for joint significance of pre-coefficients	3.49	2.48	4.11	1.62
R squared	0.399	0.560	0.407	0.402
No. of observations	947	931	947	947

Notes: District level annual data used from the Ministry of Human Resource Development for the years 2009–14. The sample is restricted to schools in the states of Bihar, Chhattisgarh, Jharkhand, Madhya Pradesh, and Orissa. All specifications control for districts fixed effects, state-specific time trends and pre-trends. Post IVRS–Pre IVRS reports the difference in the coefficients on One year after IVRS and One year before IVRS. ***, **, and * indicate significance at the levels of 1%, 5%, and 10%, respectively. Robust standard errors clustered at the district level are reported in parentheses.

percentage points) increase. This pattern remains persistent thereafter. A pre-post comparison indicates an improvement of 21 percentage points, on a baseline average of 56.2, reflecting a 37 percent change. Similar patterns are observed for enumerator-observed meal provision, as reported in columns 3 and 4. Wild bootstrap clustered confidence intervals are also included as a robustness test.

6.1.2. Official records based estimates

In Table 3, we estimate the specifications analogous to those reported in Table 1 using the official records of the Bihar state government. The outcomes are the percentage of schools serving meals and beneficiaries availing meals for primary and upper-primary schools, respectively. In contrast to Table 1, we find a statistically significant decline for both the outcome variables post-reform. A comparison of the pre-post coefficients in columns 1 and 2 reveals that after the introduction of the IVRS, the fraction of primary and upper primary schools serving mid-day meals fell by 1.4 and 5.3 percent, respectively.

In columns 3 and 4, we examine the fraction of beneficiaries availing meals in primary and upper-primary schools. One year after the program, in 2013, the fraction of beneficiaries availing mid-day meals dropped precipitously by 34 and 36.7 percent. These estimates are statistically significant at the one percent level. These patterns are also corroborated by our DID estimates reported in Table 4.

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

Another set of important outcomes is enrollment and Attendance. One of the primary objectives of the mid-day meal program in India is

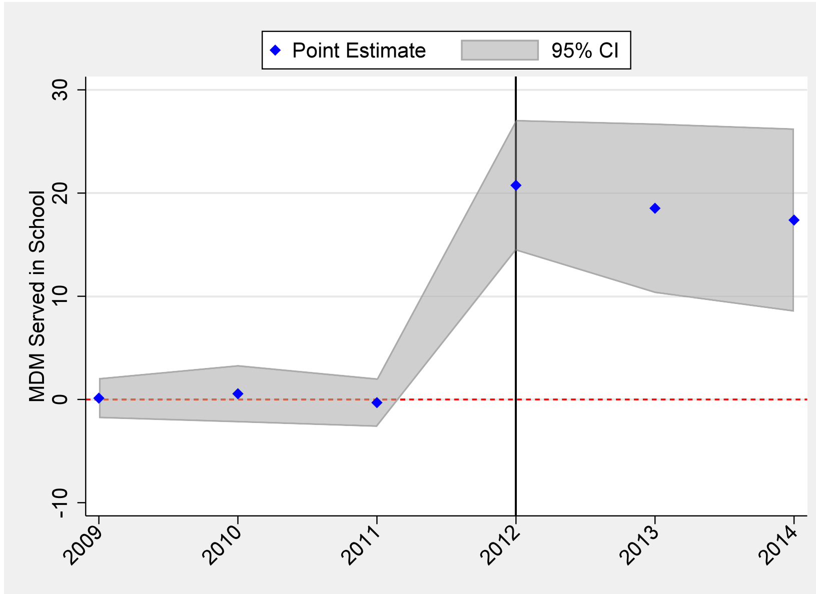


Fig. 7. Event study using SDID for MDM served in school (independent data).
Notes: We use independently collected school-level data for the years 2009–2014. The sample is restricted to the treated state of Bihar and the untreated states of Jharkhand, Orissa, Madhya Pradesh, and Chhattisgarh, and collapsed to the district level. The dependent variable "MDM Served in School" represents the percentage of schools in the district where the headmaster reported providing a meal to the survey team on the date of the survey. The graph presents results from a Synthetic DiD Regression, à la (Arkhangelsky et al., 2021), presented as an event study. All specifications control for school characteristics including the percentage of schools in the district with blackboards in grade 2, tap or hand-pump for drinking water, availability of toilets for boys and girls, and with specific school types. Bootstrapped standard errors clustered at the district level are used to present 95% confidence intervals.

to increase enrollment and attendance in schools (Afridi, 2011). These outcomes exhibit pre-trends, and therefore, the DID estimates are not reliable for these outcomes.

6.2. Results from synthetic differences-in-differences estimation

We document the results for our main outcomes of interest using SDID. Figs. 7 and 8 graph the event study for meals served and meals cooked on the day of the visit from the *Independent data*. We clearly observe that prior to the introduction of the new monitoring technology (IVRS), the SDID estimates were close to zero and statistically insignificant. In sharp contrast, we see a steep and significant increase in these outcomes in the post-period. These results are consistent with the DID-based estimates we reported previously. *Independent data* based enrollment analysis (Fig. 9) reveals that the enrollment numbers were corrected in the post period: we see negligible estimates prior to the introduction of the IVRS, but enrollment declines statistically significantly in the post period.[30] In Table 5, we show the results with standard errors for meals served, meals cooked, enrollment, and attendance using the *Independent* data. For comparison, we also report the analogous DID estimate.

Table 5 distills the results. In row 1 column (1) of Table 5, we observe that there is a 17.3 percentage point increase in a school's likelihood of providing MDM based on the *Independent data*. Moving down, we observe a 19.4 percentage point increase in the likelihood of meals being cooked (as observed by the independent team, a 39 percent reduction in enrollment, and a 14.8 percent increase in attendance. The synthetic difference in difference estimates are remarkably similar to the DID estimates reported in Column (2).

A decline in enrollment and an increase in attendance are consistent with our previous findings. As the provision of meals improved in schools, more students started attending. We find a decline in the percentage of schools providing meals and the number of beneficiaries availing these meals as per official records (Tables 3 and 4). We interpret this decline in enrollment as suggestive evidence that the IVRS curbed leakages.

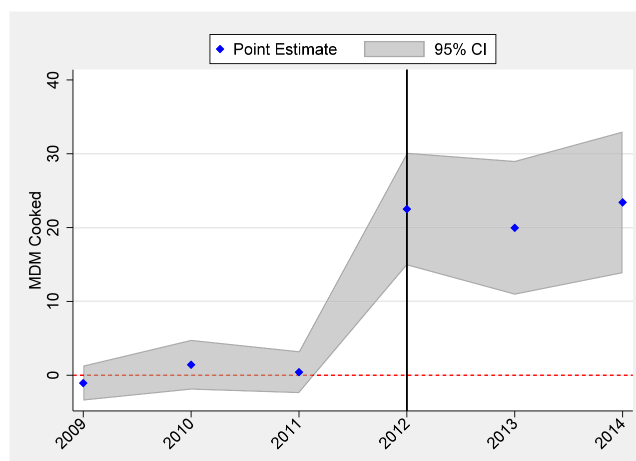


Fig. 8. Event study using SDID for MDM cooked on day of visit (independent data).
Notes: We use independently collected school-level data for the years 2009–2014. The sample is restricted to the treated state of Bihar and the untreated states of Jharkhand, Orissa, Madhya Pradesh, and Chhattisgarh, and collapsed to the district level. The dependent variable "MDM Cooked" represents the percentage of schools in the district where the meal was cooked in the school on the date of the survey. The graph presents results from a Synthetic DiD Regression, à la (Arkhangelsky et al., 2021), presented as an event study. All specifications control for school characteristics including the percentage of schools in the district with blackboards in grade 2, tap or hand-pump for drinking water, availability of toilets for boys and girls, and with specific school types. Bootstrapped standard errors clustered at the district level are used to present 95% confidence intervals.

[30] We used the STATA package SDID to construct the graphs using bootstrap standard errors.

Table 5
Synthetic differences-in-differences and differences-in-differences estimates for the main outcomes.

Main outcome	ATT of treatment on Dep. Var. using	
	SDiD	DiD
	(1)	(2)
MDM	17.300***	17.094***
	(3.323)	(3.304)
MDM cooked	19.405***	19.475***
	(3.489)	(3.478)
Total enrollment	−39.040***	−31.505***
	(6.874)	(7.148)
Total attendance	14.729***	13.315***
	(3.634)	(3.151)

Notes: We use independently collected school-level data for the years 2009–2014. The sample is restricted to the treated state of Bihar and the untreated states of Jharkhand, Orissa, Madhya Pradesh, and Chhattisgarh, and collapsed to the district level. The dependent variable "MDM" represents the percentage of schools in the district where the headmaster reported providing a meal to the survey team on the date of the survey. In contrast, the dependent variable "MDM Cooked" represents the percentage of schools in the district where the meal was cooked in the school on the date of the survey. The last two outcome variables track the average total enrollment and attendance in grades 1–5 in schools in the district. The first column presents results from a Synthetic DiD Regression, à la (Arkhangelsky et al., 2021), whereas the second column contains results from an analogous standard DiD. All specifications control for school characteristics including the percentage of schools in the district with blackboards in grade 2, tap or hand-pump for drinking water, availability of toilets for boys and girls, and with specific school types. ***, **, and * indicate significance at the levels of 1%, 5%, and 10%, respectively. Bootstrapped standard errors clustered at the district level are reported in parentheses.

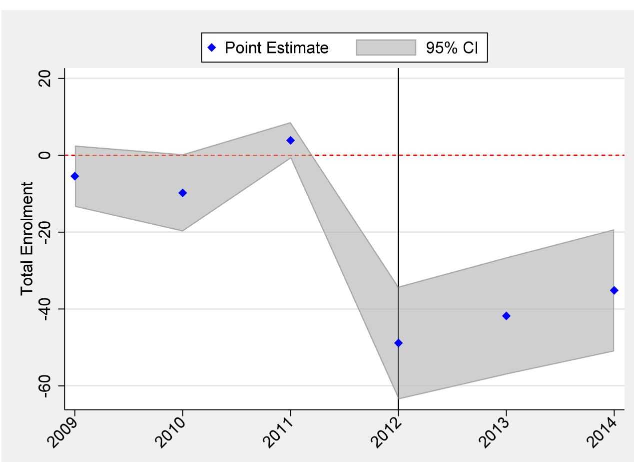


Fig. 9. Event study using SDID for total enrollment (Grades 1–5).
Notes: We use independently collected school-level data for the years 2009–2014. The sample is restricted to the treated state of Bihar and the untreated states of Jharkhand, Orissa, Madhya Pradesh, and Chhattisgarh, and collapsed to the district level. The outcome variable tracks the average total enrollment in grades 1–5 in schools in the district. The graph presents results from a Synthetic DiD Regression, à la (Arkhangelsky et al., 2021), presented as an event study. All specifications control for school characteristics including the percentage of schools in the district with blackboards in grade 2, tap or hand-pump for drinking water, availability of toilets for boys and girls, and with specific school types. Bootstrapped standard errors clustered at the district level are used to present 95% confidence intervals.

6.3. Results from the instrumental variable estimation

The 2SLS results are reported in Table 6. In Panel A, we use the number of calls completed as the endogenous variable, and in Panel B, we use call intensity (calls completed over total calls made) as the endogenous variable. The outcome variable in columns (1) and (3) is the percentage of enrolled students attending the school in a month, and it is the percentage of enrolled students who are provided meals in columns (2) and (4). Standard errors are clustered at the level of schools in columns (1) and (2) and the level of blocks in columns (3) and (4). Column (5) reports the first stage results, where we regress the endogenous variable on the instrument and the other discussed controls. We also report the Kleibergen–Paap F statistic at the bottom of each regression result in the first four columns. Column (5) shows a strong and statistically significant first stage. We find a positive and statistically significant increase in both outcomes in all specifications. An additional completed call improves attendance by 4.3% of the mean in the treatment period. A one percent change in the call intensity increases meal delivery by 0.83 percentage points (column 4, panel B) in a month. From this analysis, we conclude that the IVRS program had a causal impact on the provision of MDM provision in Bihar schools and led to an improvement. The results using the pre-post differences in enrollment are documented in Table A.5. Consistent with our previous results, we find a robust consistent decrease in reported enrollment due to IVRS.

6.4. Audit reports: Independent monitoring institutes' assessment data based estimates

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.[31] In order to conduct the DID analysis on this smaller sample, we define post as an indicator variable that takes the value of one for years 2012 onwards and zeros otherwise. We show our DID estimates in Table A.6. The fraction of schools among the audited schools that served good quality meals increased post-IVRS in Bihar relative to the other states. We find a 47 percentage points improvement in Bihar, which is highly statistically significant at the one percent significance level. This is commensurate with a decline in bad-quality meals.[32] In column 3, we report the estimate on the fraction of audited schools providing a sufficient quantity of meals. This went up by 48 percentage points, statistically significant at the 5 percent significance level. Overall, our results indicate that IVRS led to an improvement in the quality and sufficiency of the meals in Bihar.

6.5. Robustness tests for the DID estimation

To bolster our identification strategy, we conduct three robustness tests using the *Independent data*. We provide these results in Table 7. In the first panel, for ease of comparison, we show our baseline specification results condensing years into pre (2009, 2010, and 2011) and post (2012, 2013, and 2014) reform. We include a district-specific trend in this specification in addition to the district- and year-fixed effects and report the results in Panel B. The results remain remarkably similar to the estimates reported in Panel A.

In addition, we match the districts in Bihar with the districts in the control states using propensity scores which we calculate using several district-year school characteristics previously controlled for in Panel A (Table A.7).[33] We trim the observations which are outside the common support of the propensity score distribution. Figure A.3 shows the relative distributions for treated (Bihar) districts and the control (other states) districts and highlights the common support. In Panel C, we restrict the sample to this common support and estimate a DID model.[34] Our results remain unchanged. In the last panel, we use a

[31] The data does not lend itself to a pre-post reform analysis for Bihar.
[32] Since these measures in the reports are conducted from qualitative assessments, both good and bad-quality schools are reported.
[33] These school characteristics are derived from the DISE data. Since headmasters report these data to DISE and IVRS, we verify that headmasters are reporting the same information across data platforms. In Appendix Figure A.2, we plot the distribution of enrollment reported to IVRS and DISE. There are remarkably similar.
[34] We show covariate balance in Table A.7.

Table 6
IVRS and SMIP: Instrumental variable evidence.

Dependent variable	% Attendance (1)	% Meals (2)	% Attendance (3)	% Meals (4)	First stage (5)
Panel A: Endogenous variable-number of completed calls					
Completed calls	2.585**	3.369***	2.585**	3.369***	
	(1.13)	(1.00)	(1.13)	(1.00)	
Coverage					0.184***
					(0.04)
No. of observations	758742	811058	758742	811058	811058
Kleibergen–Paap F	20.2	22.2	20.1	22.2	
Average over treatment period	60	46	60	46	
SE clustering	School	School	Block	Block	
Panel B: Endogenous variable-intensity of completed calls					
Completed call intensity	0.633**	0.825***	0.633**	0.825***	
	(0.28)	(0.24)	(0.28)	(0.24)	
Coverage					0.752***
					(0.16)
No. of observations	758742	811058	758742	811058	811058
Kleibergen–Paap F	20.7	22.8	20.6	22.8	
Average over treatment period	60	46	60	46	
SE clustering	School	School	Block	Block	

Notes: We use school-level monthly-aggregated data on attendance, meals served, and number of completed calls for the period April 2012–November 2014 obtained from the IVRS system. Number of completed calls tracks how many calls the school completed in a given month. Completed call intensity is defined as the share of calls made to schools on business days which were completed by a school. % Attendance and % meals served (beneficiaries) are a percentage share of the enrollment reported by the school to IVRS for the analogous period. The coverage dummy used as the instrument is 1 for schools that are within 1 km of a village covered by a cell tower. All specifications control for village population, elevation, and terrain ruggedness. We obtained elevation data from the SRTM30 dataset (CGIAR-SRTM data aggregated to 30-second intervals), and used it to create a Terrain Ruggedness Index (TRI) as a measure of ruggedness. We exclude schools that were covered prior to the SMIP program from our analysis. All specifications control for district and month fixed effects, and district-specific time trends. Standard errors are clustered at the school level in columns 1 and 2 and at the block level in columns 3 and 4.

Table 7
Robustness check: Effect of IVRS on mid-day meals.

Dependent variable	School provides meal (1)	MDM cooked on the day of visit (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		
Diff-in-diff	0.19***	0.24***
	(0.03)	(0.03)
R squared	0.492	0.324
No. of observations	888	888

Notes: We use independently collected school-level data for the years 2009–2014. The sample is restricted to the states of Bihar, Chhattisgarh, Jharkhand, Madhya Pradesh and Orissa. All Panels control for the variables analogous to Columns (2) and (4) in Table 2. Panel A additionally controls for state-specific time trends. Panel B replaces state-specific time trends with district-specific trends. Panel C runs a DID model on a common support of the predicted propensity scores. Panel D reports the estimates from a generalized DID model using a Gaussian kernel and bootstrapped standard errors. For Panels A through D, robust standard errors clustered at the district level are reported in parenthesis. ***, **, and * indicate significance at the levels of 1%, 5%, and 10%, respectively.

generalized DID method proposed by Heckman et al. (1997) to estimate the treatment effect. We use a kernel-based matching algorithm and employ a Gaussian kernel for the procedure. We report bootstrap standard errors. Our previous results are confirmed using this specification

Table 8
DID estimate of IVRS on mid-day meal provision using independent data with sample restricted to border districts.

Dependent Var.	School provides meal		MDM cooked on the day of visit	
Baseline average	59.887	59.887	55	55
	(1)	(2)	(3)	(4)
Bihar × 2010	5.28	5.98	−5.51	−5.10
	(7.20)	(7.42)	(8.16)	(8.36)
	[−10.05, 19.93]	[−9.08, 21.55]	[−24.41, 12.73]	[−24.54, 12.31]
Bihar × 2011	4.81	5.26	−4.75	−4.41
	(8.57)	(8.39)	(8.63)	(8.31)
	[−13.14, 23.31]	[−12.66, 23.15]	[−22.96, 13.42]	[−22.76, 13.95]
Bihar × 2012	25.8**	26.0**	17.1	17.3
	(11.26)	(10.81)	(12.29)	(11.77)
	[2.21, 48.82]	[2.02, 49.14]	[−11.29, 43.51]	[−8.55, 42.21]
Bihar × 2013	36.0***	34.9***	25.8**	24.4**
	(8.22)	(7.96)	(9.68)	(9.03)
	[19.05, 53.66]	[18.35, 51.73]	[5.22, 46.39]	[4.97, 43.34]
Bihar × 2014	31.0***	31.2***	19.0*	19.1**
	(10.57)	(10.24)	(9.21)	(8.63)
	[8.72, 53.73]	[10.07, 54.22]	[−0.46, 38.60]	[0.99, 38.28]
Post IVRS–Pre IVRS	31.2***	29.62***	30.58***	28.81***
School characteristics	No	Yes	No	Yes
R squared	0.072	0.080	0.069	0.078
No. of observations	2289	2289	2289	2289

Notes: We use independently collected school-level data for the years 2009–2014 to estimate a specification identical to that in Table 2. The sample is restricted to schools in border districts (see Figure A.4) of the states of Bihar and Jharkhand. The dependent variable, school provides meal takes the value one if the headmaster reported providing a meal to the survey team on the date of the survey and zero otherwise. The other dependent variable, MDM cooked takes the value one if the meal was cooked in the school on the date of the survey and zero otherwise. 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. Post IVRS–Pre IVRS reports the difference in the coefficients on One year after IVRS and One year before IVRS. ***, **, and * indicate significance at the levels of 1%, 5%, and 10%, respectively. Robust standard errors clustered at the district level are reported in parentheses. 95% confidence intervals for the coefficients of interest from a wild cluster bootstrap analysis using district-level clustering are presented in square brackets.

as well. These tests assure us that we are not picking up the effects of confounders and that our estimates are unbiased.

Finally, we also conduct our DID analysis restricting the sample to just bordering districts that share a geographic border with Jharkhand, a state carved out of Bihar in 2000. The districts of Jharkhand that share a border with the districts of Bihar are likely to be culturally and socially more similar. Hence, these offer a better counterfactual. Appendix Figure A.4 shows the districts in Bihar and Jharkhand on the border that form our sample. The results using the independent data restricted to these border districts are reported in Table 8. The patterns are unchanged and the magnitude is even stronger. There is a significant increase in provision of MDM meals after the IVRS is rolled-out. These results bolster our previous findings. We also conducted another robustness test in which we dropped one control state at a time in our main analysis. The estimates reported in Appendix Table A.8 show that results are robust to the sample of control states we include in our analysis.

7. Cost–benefit analysis

In the previous sections, we have documented that IVRS plugged leakages in the provision of mid-day meals. In order to shed light on the sustainability of the IVR system, we conduct a cost–benefit analysis.

7.1. Is leakage completely curbed?

A point to note is that the official beneficiary statistics continue to be inflated, possibly due to inaction in monitoring and enforcement by the middle-tier officials (Figs. 5 and 6). In these figures, we observe that the official beneficiary numbers are equal to the enrollment reported by schools. The beneficiaries reported to the IVRS by the schools are lower than the enrollment. The source of savings is the update of school behavior. Schools do update the enrollment figures downward after the reform. In Table 5, we find a decline in enrollment.

7.2. Cost–benefit analysis

The state government continues to rely on the estimated beneficiary numbers reported through conventional channels.[35] These estimated numbers are mentioned in the Quarterly Progress Reports (QPRs). Despite these continued inefficiencies, as we explained above, there are benefits accruing from the IVRS due to the curbing of leakages. To quantify the gains from partial curbing of leakage, we rely on our DID estimates reported in Table 4. Columns (3) and (4) depict the decline in the percentage of beneficiaries availing the meals in primary and upper-primary schools in Bihar, respectively. From these results, we observe that the post- and pre-IVRS changes in the percentage of beneficiaries are −38.4 and −52.9 in primary and upper-primary schools, respectively. The baseline (2009 through 2011) average for *Percentage of Beneficiaries Availing MDM* is 100 percent. Government budget accounting provides a *conversion cost* per child. This is defined as the cost to feed a child an adequate MDM and is kept fixed by the government. We take our estimates of decline in the *percentage of beneficiaries* from columns (3) and (4) of Table 4, multiply it with the fixed per child *conversion cost*, and then multiply it with the baseline school enrollment to arrive at the benefit of the reform.

$$\textbf{The total benefit} = \text{Benefit from the Primary Schools} + \text{Benefit from the Upper Primary}$$

Assuming 190 working days for a typical school:

$$\textbf{Each of these benefits} = \text{Conversion Cost per child} \times \text{Baseline Number of Beneficiaries} \times (\text{Decline in Percentage of Beneficiaries}/100) \times 190$$

[35] We do not know the basis of the decision, but it can be because the directorate has not compared the two sources in terms of beneficiaries.

Table 9
Computing benefits of curbing leakages.

	Primary	Upper primary	Source
The annual average number of students enrolled in Bihar prior to the reform	214,350	78,950	APWB reports
The *conversion cost* in 2012	Rs. 3.11	Rs. 4.65	Government accounts
Percentage decline in beneficiaries	38.4	52.9	Our estimates
Savings (in Million Rs.)	25.6	19.42	Authors' computation

Using the above table and equations, the sum of benefits for the primary and upper primary equals Rs 85.5 million. This is also the pre-reform estimate of the leakage. This is just on account of *ghost beneficiaries*. Note that attendance is increasing. If we assume that the attendance increases to actual enrollment, then the share of leakages that arose from not feeding the children earlier is now going towards feeding them. Thus, there is no net increase in cost. The annual outlay of the Bihar government for the IVR system is Rs. 6 million.[36] Therefore, the annual net savings generated by the reform is Rs. 79.6 million (see Table 9).

8. Alternate hypothesis

While we emphasize fraud reduction as the reason for enhanced efficiency of the delivery program, there are alternative possibilities, but below we discuss reasons we believe these are untenable:

8.1. Fewer errors due to daily reporting

Daily reporting to the IVRS could reduce errors due to recall bias in the beneficiary information provided. As a result, the system could rely on less erroneous information than before when information was aggregated quarterly. There are two reasons to think that this is not driving our results. One, the information in the status quo system (before IVRS) was supposed to be culled from daily attendance registers maintained by the schools leaving little scope for recall bias. Second, a number of our findings are inconsistent with this being the driving reason. Independent monitoring quality and sufficiency surveys indicate an improvement in meals on both these dimensions. Independent third-party data-based findings also indicate improvements in sharp contrast to the reduction in beneficiaries reported by the official machinery. A mere improvement in reporting errors cannot result in an improvement in meal provision as indicated by independent data and, at the same time, a decline in beneficiary take-up as per official statistics.

8.2. Call serve as reminders to schools

The improvement in the take-up observed can be due to calls serving as a reminder to the headmasters. However, as per official data, the number of beneficiaries falls. If improvements were due to reminders, both official and independent data analysis would indicate improvements. Moreover, the beneficiaries reported by the headmasters/ school teachers to the IVRS depicted in Fig. 5, and those reported by the official QPRs, which form the basis of meal allocation, do not match. If there were no leakages in the system, we would expect the distributions to be similar.

8.3. Psychological effects

Another possible explanation is rooted in the psychological reaction of the agents to daily calls. If the deviant agents only shirked in the status quo and now exert effort to report the accurate beneficiary numbers, that can potentially explain why official records-based and independent survey-based results go in the opposite direction. However, this type of behavior will result in the receipt of surplus food grains and the conversion cost by the school. The school administration could either distribute these surplus resources among the existing beneficiaries or appropriate them to balance accounts and avoid detection by auditors.

9. Conclusion

This paper studies the role of IT in improving transparency and accountability in welfare programs. 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 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 a meal being cooked on the day of a surprise visit by 20 percentage points. These results are robust to several specifications, including matching-based difference-in-difference specifications and controlling district-specific trends. The increase in beneficiary take-up 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 meals in Bihar schools post IVRS and 48 percentage points in the fraction of schools serving sufficient quantity meals. In contrast, using state official records, we find that the fraction of schools serving meals and students the number of children availing MDM among enrolled students reduces post the reform's introduction. Our results provide evidence that the IVRS resulted in a 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 efficiency in a welfare program, indicating that IT solutions can increase state capacity by reforming the existing public institutions. Second, the program yielding these improvements might be portable to other arenas of public service delivery or welfare programs that have similar delivery channels. While recent RCTs have demonstrated effective use of technology at curbing corruption or increasing accountability, often when the policies are adopted at scale, the results are incongruent with expectations. Our paper shows the success of a technology-enabled reform designed and implemented by the government.

CRediT authorship contribution statement

Sisir Debnath: Data curation, Supervision, Validation, Project administration, Writing – review & editing. **Mrithyunjayan Nilayamgode:** Formal analysis, Software, Visualization, Writing – review & editing. **Sheetal Sekhri:** Conceptualization, Investigation, Methodology, Resources, Writing – original draft, Writing – review & editing.

[36] The development and operations are outsourced to a private vendor with an annual payment of 6 million Rs. The vendor absorbs the fixed costs of setting up the system.

Data availability

The authors do not have permission to share data.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jdeveco.2023.103137.

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