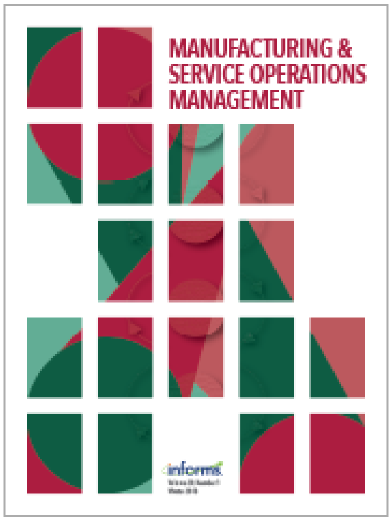

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Technology-Enabled Agent Choice and Uptake of Social Assistance Programs: Evidence from India's Food Security Program

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Abstract. ***Problem definition*:** Beneficiaries of social assistance programs with transfers of undifferentiated commodities often have a designated agent to collect their entitlements from. This gives monopoly power to agents over beneficiaries. When coupled with weak government monitoring, agents do not have incentives to adhere to stipulated operating guidelines, leading to reduced uptake by beneficiaries. Some governments are attempting to break the monopoly by allowing beneficiaries to choose agents. However, the impact of choice on uptake may be limited by lack of alternate agents in beneficiaries' vicinities, restricted ability of agents to compete with undifferentiated commodities, and collusion among agents. ***Methodology/results*:** Using a reverse difference-in-differences framework on data from a food security program in two neighboring states in India, Andhra Pradesh and Telangana, we find that providing agent choice results in a 6.6% increase in the quantity of entitlements collected by the beneficiary households. We also find that increase in uptake is about four times higher in regions with high agent density compared with those with low agent density. This emphasizes the importance of having an alternate agent in the vicinity for choice to be effective. Nearly all of the increase in uptake is attributable to new beneficiaries collecting entitlements from their preassigned agent. This is suggestive of agents improving adherence to operating guidelines in response to choice. We find associative evidence for this response in the number of days agents keep their shops open. ***Managerial implications*:** Governments executing in-kind transfers of undifferentiated commodities are piloting interventions to provide choice to their beneficiaries. Replacement of in-kind transfers with cash, an increasingly popular intervention, may be challenging in volatile markets, as the magnitude of the transfer needs to be periodically adjusted. Our results indicate that alternate designs of providing choice even in a limited form, that is, the place where the beneficiaries can collect their entitlements with products and prices fixed, can present a viable alternative.

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Keywords: food security programs • cash vs. food • biometric authentication • choice in public programs • public sector operations • empirical operations management

1. Introduction

More than 90% of low-income and about 75% of low- and middle-income countries operate social assistance programs with transfers of commodities such as food grains, cooking gas, and agricultural inputs to provide income support to their populations (Gentilini et al. 2014). Despite substantial budgetary allocations (typically about 1%–5% of the national gross domestic product; World Bank 2021), beneficiaries of these programs face several challenges in accessing their entitlements. These include difficulty in accessing an agent licensed to distribute the commodities, partial or complete denial of commodities by the agents, adulteration of commodities, and poor quality of service (World Bank 2003, Gentilini and

Omamo 2011, Khera 2011a, Gentilini et al. 2014, Dreze and Khera 2015, Pingali et al. 2019).

Most of these challenges are driven by the design of these programs, wherein beneficiaries are constrained to collect their entitlements from a preassigned agent. The preassignment is meant to facilitate authentication of beneficiary households, which until recently involved physical verification of beneficiaries' identity cards against a paper-based roster. Such preassignment accords monopoly power to agents over beneficiaries, which, coupled with weak monitoring, leaves little incentive for the agents to adhere to stipulated operating guidelines, such as number of working days in a month and working hours each day (World Bank 2003, Banerjee et al. 2018, Pingali et al. 2019). In India's food security program, the context of this study, agent preassignment is cited as one of the major reasons for a large proportion of allocated entitlements not being availed by the beneficiaries (more than 50% in some states; Khera 2011b).

Increasing deployment of digital identity systems connected to central databases (Muralidharan et al. 2016, Food and Agriculture Organization of the United Nations 2020, United Nations Department of Economic and Social Affairs 2022) can enable beneficiaries to verify their identity electronically and collect their entitlements from any licensed agent. Examples of these systems include cards fitted with an electronic chip and point-of-sale devices enabled with biometric authentication. Several countries such as India and Indonesia are leveraging this functionality to allow the beneficiaries to collect their entitlements from any licensed agent of their choice (*India Today* 2019, Kuehl 2021). Prima facie, provision of such technology-enabled choice is expected to improve access to entitlements by empowering the beneficiaries and introducing competition among agents (Bell et al. 1998, Clarke et al. 2008, Le Grand 2009, Matsa 2011). However, this argument ignores several factors that restrict the demand-side and supply-side responses to choice. For instance, on the demand side, beneficiaries may not have easy access to viable alternatives in their vicinity (Bell et al. 1998, Reisman 2001, Fusarelli 2007), many agents enjoy higher socioeconomic status over beneficiaries and may resist the implementation of choice or may collude to not serve each others' beneficiaries (Eisenhardt 1989, Bakos and Kemerer 1992, Clarke et al. 2008). On the supply side, agents may be severely restricted in their scope for competitive differentiation as the core product in these programs is provided to the agents by the government for downstream distribution and is nearly identical at all agents.

Our goal in this paper is to assess whether technology-enabled agent choice improves the uptake of commodities despite the presence of these limiting factors and elicit plausible operational mechanisms of the impact. We answer this question in the context of India's food security program, also called the Public Distribution System (PDS). Until recently, beneficiaries of the PDS could collect their grain entitlements only from a unique preassigned agent. However, several Indian states are leveraging the recently deployed digital identity systems to provide agent choice, also called *portability*, to their beneficiaries.

Our research exploits a natural experiment where two neighboring Indian states, Andhra Pradesh (AP) and Telangana (TS) (see Figure A.5 in the Online Appendix), introduced agent choice in the food security program at different points in time. AP and TS were part of an undivided state for over 60 years until 2014. AP introduced agent choice in December 2015, TS introduced agent choice in PDS in April 2018 (*India Today* 2019). We assemble a subdistrict-month[1] panel data set of 1,231 subdistricts, 659 in AP and 572 in TS, for 28 months from January 2017 to April 2019, from publicly available data sources. This data set contains information on the total grain entitlement (quantity allocated), quantity availed by beneficiaries, and number of agents in each subdistrict-month combination. We use a reverse difference-in-differences (DID) framework (Kim and Lee 2019) because, unlike the usual DID, intervention (agent choice) in our setting was introduced in the control group (AP) nearly two years before the start of our study period, and in the treatment group (TS) midway during our study period. The reverse DID estimator measures pretreatment differences between AP and TS assuming parallel trends after the introduction of choice in TS.

We find that the introduction of agent choice increased the uptake by 20,273 kg at a subdistrict-month level, a 6.6% increase in the quantity of entitlements collected by the beneficiary households. This increase translates to 810 more beneficiary households per subdistrict on average who were not accessing their entitlements previously, now doing so. These beneficiaries experience direct cost savings of INR 600–700 per month, ~20% of the average household expenditure on food per month, assuming they would have purchased the equivalent quantity from the open market at market price otherwise (National Council of Applied Economic Research 2015). To confirm that our results are not due to plausible unobserved confounding factors, we use two matching strategies: *proximity-based matching*, where we compare subdistricts that lie along the state boundary, and *development-based matching*, where we compare subdistricts with similar socioeconomic development measured as luminosity levels in night-light data (Henderson et al. 2012). Our results remain robust to both matching strategies.

Next, to elicit plausible mechanisms leading to the increased uptake, we collect two additional data sets from publicly available sources: first, subdistrict-month panel data of the number of choice users in our treatment state after the introduction of choice from April 2018 to April 2019, and second, the number of days an agent keeps the shop open in each month in the control state from March 2018 to August 2018.

Using the choice users data, we estimate the percentage of increase in uptake that can be attributed to beneficiaries exercising choice, that is, collecting their entitlements from an agent other than their preassigned agent. A larger percentage implies that choice improves uptake by enabling beneficiaries to access other agents in the state, whereas a lower percentage implies that choice improves uptake by enabling beneficiaries to access the preassigned agent. The latter is indicative of choice having a self-monitoring effect on agents, who improve compliance with operating guidelines such as number of days the shop is kept open, after the introduction of choice.

We find that nearly all of the 810 additional beneficiaries accessing their entitlements after the introduction of choice collect grains from their preassigned agents. This is suggestive of an improvement in beneficiaries' access to their preassigned agents, possibly due to increased compliance of agents with stipulated operating guidelines. We posit that improved compliance among agents is likely to be in anticipation of losing their preassigned beneficiaries to other agents in the vicinity as they no longer enjoy monopoly benefits. We validate this supposition by comparing the impact of choice in regions with high and low agent density. We find that the impact is 400% higher in the former, where the cost of exercising choice is low for beneficiaries, compared with the latter.

Using the data on the number of days an agent keeps the shop open, we provide associative evidence from two analyses to demonstrate that the provision of agent choice is likely to have resulted in agents' increased compliance with stipulated operating guidelines. In the first analysis, we measure the association between uptake at an agent and the number of days the neighboring agent keeps their shop open. We find a negative association indicating that beneficiaries choose agents that keep their shops open for a larger number of days in a month. In the second analysis, we measure the association between the number of days an agent keeps the shop open and the number of days the neighboring agents kept their shops open in the previous month. We find a positive association, indicating that agents respond to other agents in the vicinity keeping the shops open for longer by keeping their shop open for more days. Collectively, we attribute these associations to beneficiaries exercising their agency, resulting in agents responding to choice by keeping their shops open for a larger number of days in a month. Furthermore, we find that the magnitudes of the associations in both analyses decrease with the distance between the agents, reinforcing our finding that agent choice is likely to be effective when the cost of accessing an alternate agent for the beneficiaries is low.

In summary, our results suggest that the impact of technology-enabled agent choice on the uptake of commodities in social assistance programs is positive. We show that existence of such choice alone has a positive impact on uptake even if beneficiaries do not exercise it, and the impact is likely to be due to agents responding to choice with improved adherence to service standards. These results bear important implications for developing countries (e.g., Mexico, Egypt, Sri Lanka, and Indonesia) with social assistance programs like the PDS with in-kind transfers of commodities, which are piloting interventions to provide choice to beneficiaries. One intervention that is being widely adapted (and debated) is the complete replacement of in-kind transfers with cash transfers, which provide beneficiaries with the freedom to purchase whatever they want, whenever they want, and from whomever they want (Del Ninno et al. 2007, Hidrobo et al. 2014, Kuehl 2021). However, there is no clear consensus on whether cash transfers outperform in-kind transfers in improving beneficiary welfare (Gentilini 2016, Mukherjee et al. 2023). Our results show that an intermediate design of choice wherein governments provide the freedom of *where* to avail entitlements to beneficiaries while still controlling *what* and *how much* is being availed can have substantial impact on the uptake of commodities by the shifting the power from the agent to the beneficiaries. With many low-income and low- and middle-income countries actively investing in digitalization (United Nations Department of Economic and Social Affairs 2022), designing such intermediate configurations of choice is an increasingly feasible option for governments to consider.

2. Literature Review

Our paper relates to two streams of research: agent compliance in public programs and food supply chains in developing economies.

2.1. Uptake and Agent Compliance in Public Programs

Our study extends literature on operational strategies to increase uptake of public programs and services. Buell et al. (2021) use a field experiment to demonstrate that increasing operational transparency by displaying pictures of agents working behind the scenes increases the use of a government's mobile application for submitting service requests to the city's public works department. A related stream of literature in economics focuses on the role of centralized monitoring on increasing agent compliance and uptake. Muralidharan et al. (2021) find that uptake of an agricultural cash transfer program increased in regions where authorities sought direct feedback about agents from beneficiaries by calling randomly chosen telephone numbers. Duflo and Hanna (2005) find that student dropout rates decreased in public schools where third-party nongovernmental organizations were employed by the government to monitor teacher attendance. Muralidharan et al. (2020) and Ganesh et al. (2019) find that monitoring transactions between agents and beneficiaries using biometric authentication devices increases uptake of food grains by reducing diversion into the open market by agents in a government food security program.[2]

Our study complements this literature by shifting the focus from supply-side mechanisms that monitor compliance of agents interacting with beneficiaries to a demand-side, nonmonitoring mechanism that empowers beneficiaries with choice. In this regard, our work closely relates to that of Hoxby (2000). Using an instrumental variable approach, Hoxby (2000) finds that enrollment rates in public schools are higher and those in private schools are lower in regions where households have more public schools to choose from. The increase is attributed to competition among public schools. Our study extends this paper by demonstrating that choice increases uptake even in public services where the scope for competitive differentiation is limited. The core product (food grains) in our study setting is nearly identical at all agents, and therefore, it is ex ante unclear whether agent choice will be meaningful. We show that choice increases uptake even in such contexts.

2.2. Food Supply Chains in Developing Economies

The focus of most of the work in this stream is analyzing interventions to improve farmers' decision making in upstream food supply chains (Dawande et al. 2013, Chen and Tang 2015, Parker et al. 2016, Levi et al. 2019, Liao et al. 2019, Chintapalli and Tang 2021). For instance, Parker et al. (2016) find that timely and accurate information on daily market prices provided through a text message service reduces geographic price dispersion. Levi et al. (2019) show that farmer's revenue in online agricultural platforms can be increased using novel auction designs that enable innovative price discovery mechanisms. Other studies have also examined strategies to deter adulteration in upstream food supply chains (Mu et al. 2016, Levi et al. 2020). For instance, Levi et al. (2020) analyze how quality uncertainty, supply chain dispersion, traceability, and testing sensitivity jointly impact the equilibrium adulteration behavior. Mu et al. (2016) propose novel strategies to minimize testing while achieving a socially desirable equilibrium. These studies attempt to address the issues of farmers/suppliers upstream, whereas the challenges faced downstream by end customers, especially beneficiaries of government-managed food distribution programs, have not received adequate attention. We contribute to this literature by focusing on these beneficiaries, who often represent the bottom of the pyramid (BoP) and are comparable in size to farmer households (Damodaran 2021, Mahajan 2021).

3. Background

In this section, we provide a brief description of India's food security program, the PDS; implementation of agent choice; and our study setting.

3.1. India's Food Security Program

India's food security program, also called the Public Distribution System, aims to provide adequate quantities of essential food commodities such as rice to economically underprivileged households. The government determines the adequate quantity for each household based on the number of individuals in the household and its economic status. This is referred to as the entitlement quantity for that household.[3] Hereafter, we use the terms *beneficiaries* and *beneficiary households* interchangeably to represent households for whom the government allocates an entitlement quantity.

Under this program, close to 160 million households are entitled to receive a fixed quantity of food grains each month at heavily subsidized prices (at INR 1–3 per kilogram compared with market prices of INR 25–40 per kilogram) from licensed agents operating fair price shops (FPSs). In 2021, India spent close to 7% of its national budget (~USD 0.5 trillion) on the program. In this section, we elaborate the operations of this program in two parts. The first part includes a description of agent assignment, and the second part includes a description of agent operations and incentives every month.

3.1.1. Agent Assignment. The government identifies locations to install FPSs and invites individuals to apply for a license to operate the shops. Each FPS has about 300–400 households assigned to it and is located approximately at the geographic centroid of these households to enable easy access (Institute for Competitiveness 2022).

A typical applicant is expected to show availability of a space suitable for storing grains and running the shop. The applicant is also expected to make a deposit of INR 50,000, which is refunded at the end of the license period, which is typically two to three years. Upon physical verification of the space, the government assigns the contract to run the FPS and the individual becomes an agent.

We learned from our field visits that the applicants are typically microretailers in the neighborhood or individuals residing in permanent dwellings willing to apportion some space for running the FPS. We also gathered that for most agents, running the FPS is a part-time vocation.

3.1.2. Agent Operations.

The government expects every licensed agent to keep the shop open for the first 15 days of the month and provide all beneficiaries that visit the shop with the quantity of grains allocated to them. At the end of the 15 days, the agent is expected to place an order for additional grains for the next month. Central planners suggest the order quantity based on the number of households assigned to the agent, their allocations, and the inventory on hand.

To place the order, the agent visits the grain storage warehouse, provides his or her biometrics, and makes a security deposit. The deposit amount is a constant multiple of the order quantity and is reimbursed at the end of the month after the agent disburses grains to households.

Agents receive a commission on INR 1 for every kilogram of grain disbursed. With an average household allocation at ~25 kg, this translates to a monthly income of INR ~7,500–10,000 each month, slightly lower than the average monthly wage earned by self-employed workforce in rural India (Institute for Competitiveness 2022). The government bears the cost of shipping grains to the shop.

3.2. Implementation of Agent Choice

State governments introduced agent choice to curb the monopoly power accorded to agents due to preassignment of beneficiaries to the nearest agent (*India Today* 2019). The monopoly power is attributed to issues such as frequent shop closures, denial of entitlements, overcharging or not disbursing the entire quantity, mistreatment of beneficiaries by the agents, and long queues, leading to several beneficiaries being unable to collect their entitlements (Vaidya and Somasekhar 1998, Khera 2011a, Dreze and Khera 2015, Sati 2015, Sharma and Gupta 2019). Though grievance redressal mechanisms and vigilance committees exist, only an estimated 1.5% of the beneficiaries across the country are aware of these redressal mechanisms (National Council of Applied Economic Research 2015).

The introduction of agent choice was made possible by the end-to-end digitization of the program's supply chain, which involved the provision of digital identities such as chip-based electronic cards to beneficiaries and the installation of point-of-sale devices connected to central databases at the fair price shops (Allu et al. 2019). As of 2019, around 10 states had used the digital infrastructure to allow beneficiaries to authenticate their identity and collect their entitlement from any licensed agent in the state. This provision is termed portability and was expected to provide convenience to beneficiaries.

Intuitively, providing beneficiaries with choice should increase uptake, as intended by the government, but key operational aspects of the program may limit the impact. First, given that the government installs an FPS at an approximate geographical centroid of 300–400 households, presence of more than one agent in the neighborhood is less likely in more sparsely populated regions. Ganesh et al. (2022) find that ~27% of the beneficiaries in our control state do not have an alternate agent within a 1 km radius of their currently assigned agent. In such neighborhoods, choice is likely to be less effective, as the beneficiaries incur substantial transportation costs to access other agents. Second, serving additional households may entail ordering and stocking a higher quantity of grains for the month, thereby increasing the working capital needs of the agent due to a higher security deposit. Furthermore, agents, who are typically microretailers or home dwellers, are often constrained by the space to store the additional grain. Thus, even if the agent intended to cater to more beneficiary households after introduction of choice, the economic and operational feasibility remains unclear. In a national survey, 28% of agents revealed that they did not serve beneficiaries not preassigned to them because of fear of running out of stock, and 10% of agents reported at least one instance of stockout in the last three months due to increased demand variability after the introduction of choice (Dalberg 2022). Relatedly, Joshi et al. (2016) and Rajan et al. (2016) also report agents colluding with each other to not honor beneficiaries preassigned to one another in the state of Chhattisgarh.

We substantiated the existence of these issues in our study setting (described in Section 3.3) by conducting semistructured interviews with agents, government officials, and beneficiaries (see detailed interview guides in the Online Appendix, Section A.8). We observed three key factors limiting the potential of agent choice on uptake. First, we observed agent noncompliance wherein they either colluded to deny grains to beneficiaries who were not preassigned to them or tampered with the weighing scale to provide only a fraction of the beneficiaries' entitlement while the system recorded the full entitlement as being distributed. Second, officials in both states confirmed that the replenishment policy had not changed significantly after the introduction of agent choice. Although beneficiaries are free to avail their food grains from any agent, there is still a notional assigned agent for each beneficiary, and inventory replenishment decisions continued to be based on the notional assigned agent. Agents are free to order more than the quantity recommended by the central planners. However, we did not encounter any agent doing so. Third, rural beneficiaries had less freedom compared with beneficiaries in urban regions to use agents other than their preassigned agents because of accessibility. The presence of these challenges and the extent to which they affect access to food grains make the impact of agent choice on beneficiaries' ability to access entitlements an empirical question.

3.3. Study Setting

Our study is based in two neighboring Indian states, Andhra Pradesh and Telangana, which introduced portability at different points in time. It is noteworthy that the two states had existed as a combined state for over 60 years before their separation in 2014. Hence, unobserved aspects such as beneficiaries' sociocultural habits are likely to be similar across both states, strengthening the validity of our empirical results.

In both AP and TS, introduction of agent choice closely followed the installation of biometric devices connected to central databases at FPSs. This infrastructure can be used to authenticate a beneficiary from his or her fingerprints/iris scans. AP completed the installation of biometric devices by October 2015 and introduced portability in December 2015. TS completed the installation of biometric devices by March 2018 and introduced agent choice in April 2018. Agents in both AP and TS called for a statewide strike in response to the introduction of choice and demanded higher commissions from the government (*The New Indian Express* 2015, *Times of India* 2018), illustrating some of the contextual factors that make it necessary to empirically estimate the impact of agent choice on uptake of entitlements.

4. Data

We assembled three data sets—an uptake data set, a choice users data set, and a shop open days data set—from web portals owned and managed by the Department of Consumer Affairs, Food and Civil Supplies of AP (control state) and TS (treatment state).

4.1. Uptake Data Set

This data set contains the total quantity of grains collected by the beneficiaries (uptake), quantity allocated to beneficiaries by the government, and number of agents at the subdistrict-month level for 1,231 subdistricts, 659 in AP and 572 in TS, for a period of 28 months from January 2017 to Apri1 2019.

AP published these data for all 659 subdistricts in all 28 months (18,452 subdistrict-month observations). TS published these data for each of its 572 subdistricts after all agents in that subdistrict received biometric devices (9,780 subdistrict-month observations). Figure A.6 in the Online Appendix shows the rollout of biometric devices in TS over time. It is noteworthy that unlike for AP, we do not have a balanced panel for TS. During our analysis time period, TS started providing its agents with biometric authentication devices. We observe uptake in each subdistrict of TS only after all agents in that subdistrict received biometric devices.

We exploit a natural experiment to estimate the impact of agent choice on uptake. Uptake is a reasonable measure of welfare, as each additional kilogram of grain collected from the program results in a direct household cost savings of INR 25–30, the market price if a beneficiary were to purchase it from the open market.[4] Conservatively, this amounts to an hour's minimum wage in India[5] and constitutes slightly over 1% of a household's expenditure on food (National Council of Applied Economic Research 2015).

Table 1, panel A, contains summary statistics of key variables in the data. During our study period, the average monthly entitlements of food grains per subdistrict were 330,470 and 295,492 kg in TS and AP, respectively. Of the allocated amounts, monthly averages of 296,168 and 289,207 kg were collected by beneficiaries in TS and AP, respectively. In Table 1, panel B, we provide model-free evidence of the impact of agent choice in our treatment state. The average percentages of entitlements collected in the four groups of subdistrict-months, control and treatment before and after April 2018, are 98.70%, 88.96% and 97.05%, 89.51%, respectively. This suggests that the impact of agent choice unconditional on other covariates is a 2.2 percentage point increase in the proportion of entitlements collected by the beneficiaries.

Table 1. Summary Statistics on Key Operational Variables of Interest

	AP (control)	TS (treatment)
Panel A. Summary statistics		
Uptake (kg)	289,207 (248,146)	296,168 (330,961)
Quantity allocated (kg)	295,492 (250,688)	330,470 (364,543)
Number of choice users	—	2,103 (6,140)
Number of subdistricts	659	572
Subdistrict-month observations	18,452	9,780
Panel B. Model-free evidence for % of entitlements collected		
Before April 2018 (%)	98.70	88.96
After April 2018 (%)	97.05	89.51
First differences (%)	−1.65	0.55
Difference in differences (%)	2.2	

Notes. All numbers for uptake and quantity allocated represent averages over all observations at the subdistrict-month level. The standard deviations are shown in parentheses. Other summary statistics are included in the Online Appendix, Table A.1. Model-free evidence is shown for subdistrict-months that are completely digitized.

4.2. Choice Users Data Set

This data set contains the total number of beneficiaries collecting their grain from an agent other than their preassigned agent, henceforth referred to as *choice users*, from Apri1 2018 to April 2019 in our treatment state (TS). The data are obtained for 572 subdistricts in TS and contains 5,833 subdistrict-month observations. Unfortunately, similar data for AP were not publicly available for our analysis time period. Around 17% of the beneficiaries in TS (2,103 beneficiaries) exercised choice on average every month in each subdistrict.

4.3. Shop Open Days Data Set

This data set is an agent month panel that contains the number of days an agent keeps the shop open and the uptake at the agent in our control state (AP) for six months, from March 2018 to August 2018. The data include all 26,413 licensed agents in our control state. During our study period, the average monthly uptake at an agent is 7,013 kg, and the average number of shop open days each month is 12.6 days. We also obtain the shop addresses, from which we extract the geolocation data (latitude and longitude) of each shop. Similar data are not published by our treatment state (TS).

5. Impact of Agent Choice on Uptake

In this section, we describe our identification strategy, present our econometric models, and discuss the results. For brevity, we present additional robustness checks in the Online Appendix.

5.1. Identification Strategy

We use a reverse difference-in-differences approach to estimate the causal effects (Kim and Lee 2019). In contrast to typical settings that use DID to estimate the impact of an intervention, in our setting, the control group is the one that always had the intervention applied, that is, always had agent choice, over the study period, whereas the treatment group received the intervention in April 2018, midway through the study period. As a result, the treatment and control groups in our setting are comparable *after* the intervention is implemented in the treatment group instead of *before*. Although the estimation procedure is similar to that of conventional DID, the parallel trends assumption in the reverse difference in differences needs to hold after the intervention.

In our context, the parallel trends assumption is unlikely to hold immediately after the introduction of choice in TS. Agents, beneficiaries, and central planners in TS would have taken a few months to adapt to the introduction of agent choice after April 2018, whereas such adaption might have already happened in AP by the beginning of our study period. For instance, beneficiaries in TS may have gradually learned about agent-level service standards from their own experiences and of those in their social contacts to choose their preferred agent (Davis et al. 2021). Therefore, we follow Besley and Burgess (2004) and add group-specific time fixed effects to accommodate different time trends across the two states. Conditional on the group-specific time trends, we find evidence for parallel trends being satisfied using an event study specification. We elaborate our tests for parallel trends in Section 6.1 after describing our main model and results in this section.[6]

5.2. Main Model

We implement the reverse DID framework using the following regression specification:

$$UPTK_{it} = \alpha_i + \beta_t + \delta CHC_{it} + \theta_1 QA_{it} + \theta_2 STRK_{it} + \gamma D_{st} + \epsilon_{it}, \quad (1)$$

where subscripts i and t index the subdistricts and months, respectively. The variable $UPTK_{it}$ denotes the total quantity of grains collected by beneficiaries in subdistrict i in time t. The variable CHC_{it} is an indicator variable to denote whether agent choice was enabled in a subdistrict in our treatment state. It takes a value of one if a subdistrict i belongs to TS and the period t is after April 2018, and zero otherwise. Coefficients α_i and β_t capture time-invariant aspects specific to each subdistrict and subdistrict invariant time fixed effects, respectively. Time-invariant subdistrict fixed effects include factors such as the general efficacy of central planners in executing the food security program, and relative affluence of beneficiaries and their dependence on subsidized grain, whereas subdistrict invariant time fixed effects include factors such as agricultural and festive seasons, both of which have been shown to impact the uptake of subsidized grain (*Economic Times* 2009, Dharmapuri District Administration 2021). The variable D_{st} captures state-specific time fixed effects included to account for time trends described in Section 5.1. We also control for quantity allocated (QA_{it}) to beneficiaries in subdistrict i in month t, as a higher allocated quantity corresponds to more beneficiaries in the subdistrict and therefore higher uptake, all else being the same. Finally, we also add a binary variable ($STRK_{it}$), which takes the value one for subdistricts in TS from June to August 2018 when agents in TS went on strike, causing a drop in recorded uptake. The coefficient δ quantifies the average treatment effect of introducing agent choice on uptake of food grains by beneficiaries in the PDS.

Results from estimating Equation (1) are shown in column (1) of Table 2. We find that introduction of agent choice increases monthly uptake of entitlements in a subdistrict by 20,273 kg. The average quantity allocated by the government to beneficiaries in a subdistrict

Table 2. Average Effect of Agent Choice

	(1) Uptake (kg)	(2) $UPTK_{it}/QA_{it}$
Impact of agent choice (δ)	20,273.82***	0.053***
	(1,975.32)	(0.003)
Impact of quantity allocated (θ_1)	0.94***	—
	(0.01)	
Impact of strike (θ_2)	−11,362.66***	−0.027***
	(1,349.59)	(0.003)
Adjusted R^2	0.898	0.19
Observations	28,232	28,232

Notes. Results shown are for subdistrict-month panel regressions with subdistrict and month fixed effects, state time dummies, and standard errors clustered at the subdistrict level. Column (1) shows the results from estimating (1) with the dependent variable *Uptake*. Column (2) shows results from estimating (1) with the dependent variable $\frac{UPTK}{QA}$ and excluding QA_{it} as a covariate.

$^{***}p < 0.01$.

each month after the introduction of choice in our treatment state is 308,080 kg. Consequently, the impact of choice on uptake estimated from Equation (1) represents a 6.6% increase in the entitlements collected by beneficiary households in treatment state, after the introduction of agent choice. We note that the estimated 20,273 kg is the overall increase in uptake due to introduction of agent choice and includes a potentially negative impact that agent choice may have on uptake due to beneficiaries being unable to collect their grains because of stockouts (see the Online Appendix, Section A.2, for a discussion on stockouts at agents).

The increase in uptake estimated from Equation (1) could be due to either an increase in the quantity of grains received by each beneficiary (intensive margin) or an increase in the number of beneficiaries collecting their entitlements (extensive margin), or a combination of both. Evidence from our field visits suggests that secondary data sources do not capture change in intensive margin as agents record the quantity disbursed as the total entitlement, even if the actual disbursed quantity is less than the entitlement.[7] We verify this observation using a beneficiary-level transaction data set obtained from Ganesh et al. (2022), which shows that 99.98% of beneficiary transactions recorded beneficiaries collecting full entitlements (see the Online Appendix, Section A.3, for a description of the data). Therefore, increase in the uptake due to introduction of choice can be attributed to an equivalent increase in the number of beneficiaries collecting their entitlements. Given that the average entitlement per beneficiary is 25 kg,[8] it translates to 810 (20,273/25) additional beneficiaries collecting their entitlements from the PDS every month in each subdistrict after the introduction of choice.

Admittedly, literature on India's food security program extensively documents that agents often manipulate weighing scales to show a higher amount than the actual weight, selling the difference in the open market (see Khera 2011a, b). The introduction of agent choice allows the beneficiaries to collect their grains from agents who do not engage in such fraud, and, therefore, they may witness an increase in the actual quantity of grain collected, that is, the intensive margin. However, such increase is not captured in the sales records and, therefore, is not a part of our estimated effect size.

Last, we also estimate an alternate specification with the ratio of allocated grains collected by beneficiaries ($\frac{UPTK_{it}}{QA_{it}}$) as the dependent variable and drop QA_{it} as an independent variable in the estimation. Results of this estimation shown in column (2) of Table 2 indicate that introduction of agent choice increased the proportion of grain entitlements collected by the beneficiaries by 5.3 percentage points. We also estimate the impact of agent choice on uptake by excluding and winsorinzing potential outliers at the 1% level on both tails and find that the impacts are 17,812.63 kg and 18,286.55 kg, respectively. Corresponding values for the ratio of allocated grains collected are 0.042 and 0.047, respectively. Results are shown in Tables A.2 and A.3 in the Online Appendix.

5.3. Role of Agent Density

In this section, we study the moderating role of agent density on the impact of choice on uptake. The introduction of choice is likely to have a meaningful impact only if beneficiaries have an alternate agent in the vicinity. We hypothesize that the density of agents moderates the impact of agent choice on uptake, as the cost of accessing alternate agents is lower for beneficiaries in regions with high agent density. Specifically, we expect the impact of choice on uptake to be higher in subdistricts with high agent density in comparison with those with a low agent density, ceteris paribus.

We measure agent density in a subdistrict (DEN_i) as number of agents per square kilometer in a subdistrict. We obtain data of the area of a subdistrict from the Village and Town Amenities data set of the *District Census Handbook* published by the Office of the Registrar General and Census Commissioner, India. For ease of interpretation of the results, we convert agent density into a binary variable that takes the value one if agent density in the subdistrict is greater than the 75th percentile and zero otherwise,[9] and estimate the following triple difference model:

$$UPTK_{it} = \alpha_i + \beta_t + \delta CHC_{it} + \phi CHC_{it} \times DEN_i + \theta_1 QA_{it} + \theta_2 STRK_{it} + \gamma D_{st} + \epsilon_{it}. \quad (2)$$

The coefficient δ is the impact of providing choice in low-density subdistricts, and $\delta + \phi$ is the impact of providing choice in high-density subdistricts.

Table 3. Moderating Role of Agent Density on the Impact of Agent Choice on Uptake

	(1) Base model	(2) Interaction with agent density DV (*UPTK*)	(3) Interaction with agent density DV ($\frac{UPTK}{QA}$)
Overall impact of agent choice (δ)	20,273***	16,295***	0.049***
	(1,975)	(2,178)	(0.0036)
Incremental impact in high-density areas (ϕ)		43,734***	0.038***
		(12,399)	(0.006)
Impact of quantity allocated (θ_1)	0.94***	0.94***	
	(0.01)	(0.01)	
Impact of strike (θ_2)	−11,362.66***	−11,392***	−0.027***
	(1,349.59)	(1,350)	(0.003)
Adjusted R^2	0.898	0.901	0.194
Observations	28,232	28,180	28,180

Notes. Results shown are for subdistrict-month panel regressions with subdistrict and month fixed effects, state time dummies, and standard errors clustered at the subdistrict level. Column (1) shows the overall impact (results from estimating (1) with the dependent variable *Uptake*). Column (2) shows the incremental impact in high-density areas (results from estimating (1) with the dependent variable *Uptake*). Column (3) shows the incremental impact in high-density areas (results from estimating (1) with the dependent variable $\frac{UPTK}{QA}$ and excluding QA^{it} as a covariate. We drop one subdistrict in our control state because of the unavailability of data on its area. Consequently, the number of observations in columns (2) and (3) drops to 28,180.
***$p < 0.01$.

Column (2) of Table 3 shows results of this estimation. As expected, we find that the impact of choice in subdistricts with low agent density is 16,295 kg (δ), and the incremental impact in subdistricts with high agent density is 43,734 kg (ϕ). The total impact of providing agent choice on uptake in subdistricts with high agent density is 60,029 kg ($\delta + \phi$). Our results remain robust to alternate specification using uptake as a percentage of QA_{it} as our dependent variable. Results of this estimation are shown in column (3) of Table 3. These results suggest that impact of providing agent choice is significant even in subdistricts with low agent density; however, higher agent density substantially magnifies this impact by almost four times.

We also estimate (2) using an alternate definition of DEN_i as subdistricts identified as urban in the district census data set published in 2011. Given that urban regions have a larger concentration of population, agent density is also higher in those regions.[10] Our results are consistent with this alternate definition and are relegated to Table A.6 in the Online Appendix for brevity.

5.4. Potential Mechanism

In this section, we explore plausible changes in agent and beneficiary behavior that may be driving the impact of agent choice on uptake. Surprisingly, we find that the introduction of agent choice increases uptake by enabling more beneficiaries to collect grains from their own preassigned agents. We describe this analysis in Section 5.4.1. We posit that this is indicative of agents responding to choice by improving their compliance with stipulated service standards such as the number of days they keep their shops open in anticipation of losing beneficiaries and associated compensation to other agents in the vicinity. In Section 5.4.2, we provide associative evidence to demonstrate this agent behavior. In the absence of choice, we expect agents' decisions on the number of days to keep their shops open to be independent of each other as they cater to different sets of preassigned beneficiaries. However, we find a positive correlation between the number of days an agent keeps the shop in a month and the number of days the neighboring agents kept their shops open in the previous month. We interpret the positive correlation as choice inducing a threat of losing beneficiaries to other agents in the vicinity who keep their shops open longer.

5.4.1. Increase in Uptake Attributable to Choice Users. We use the choice users data set, a subdistrict-month panel of the number of choice users in our treatment state from April 2018 to April 2019, to estimate the increase in $UPTK_{it}$ associated with the number of beneficiaries exercising choice (CU_{it}). We posit that a lower value of this association indicates beneficiaries being able to access their own preassigned agents because of improved adherence to stipulated operating guidelines such as the number of days and/or hours of the day the shop is kept open. In contrast, a larger value of this proportion is indicative of agent choice increasing uptake by allowing beneficiaries who were unable to access their entitlement from the preassigned agent to collect their entitlements from other agents in the

Table 4. Association Between Number of Choice Users and Uptake

	(1) Uptake (kg)
Impact of choice users (δ')	0.00
	(0.18)
Impact of quantity allocated (θ_1)	0.92**
	(0.10)
Impact of strike (θ_2)	−2,044.60***
	(635.73)
Adjusted R^2	0.99
Observations	5,992

Notes. Results shown are for subdistrict-month panel regressions with subdistrict and month fixed effects with robust standard errors. The results are from estimating (3) with the dependent variable *Uptake*.
**$p < 0.05$; ***$p < 0.01$.

state. We estimate the association using the following specification:

$$UPTK_{it} = \alpha_i + \beta_t + \delta' CU_{it} + \theta_1 QA_{it} + \theta_2 STRK_{it} + \epsilon_{it}, \tag{3}$$

where δ' captures the increase in *uptake* associated with an additional choice user.

Results of this estimation are shown in column (1) in Table 4. We find that increase in uptake in a subdistrict for an additional choice user in that subdistrict is nearly zero and statistically insignificant; that is, we do not find evidence of new beneficiaries exercising choice. This means nearly all of the increase in uptake estimated from the main model (20,273 kg) can be attributed to new beneficiaries collecting grains from their own preassigned agents, thereby indicating that agents may have responded to choice with better adherence to the stipulated operating guidelines making it easier for the beneficiaries to access them.

From an operational point of view, a large proportion of increase in uptake coming from beneficiaries using their preassigned agents suggests introduction of choice may not have led to significant increase in demand variability experienced by agents. Consequently, the inventory required to manage demand variability may not be very high, suggesting the operational costs of implementing agent choice may not be very high.

5.4.2. Uptake at an Agent and Adherence to Stipulated Operating Guidelines. We propose two associative studies using the shop open days data set—an agent-month panel of the number of days an agent keeps the shop open in our control state from March 2018 to August 2018—to demonstrate that beneficiaries exercising choice may have resulted in agents keeping their shops open for more days in a month. The government stipulates all agents must keep their shops open for the first 15 days of each month. However, several studies report shops not being open during the stipulated duration of time as one of the major beneficiary concerns with the program's service quality and agent behavior (Vaidya and Somasekhar 1998; Khera 2011a, b; National Council of Applied Economic Research 2015; Sati 2015).

In what follows, we describe the two studies: (1) association between the uptake at an agent and the number of days the neighboring agents keep their shops open and (2) the association between the number of days an agent keeps the shop open and the number of days other agents in the neighborhood keep their shops open.

Uptake at an Agent and the Number of Shop Open Days of the Neighboring Agents. In the absence of agent choice, we expect uptake at an agent to be independent of the number of shop open days of the neighboring agents. However, if the beneficiary can choose an agent, we expect uptake at the focal agent to be negatively associated with the number of days neighboring agents keep their shops open. That is, the uptake at the focal agent is lower when neighboring agents keep their shops open for longer. Furthermore, given that the beneficiaries are less likely to use agents that are farther away because of higher cost of access, we expect the strength of the association to decrease with distance between the focal agent and the neighboring agents. We estimate the associations using the following specification:

$$\begin{aligned} UPTK_{st} = {} & \alpha_s + \beta_t + \gamma_0 OPENDAYS_{st} \\ & + \gamma_{s_{0-1}} \overline{OPENDAYS}_{s_{0-1},t} + \gamma_{s_{1-2}} \overline{OPENDAYS}_{s_{1-2},t} \\ & + \gamma_{s_{2-3}} \overline{OPENDAYS}_{s_{2-3},t} + \gamma_{s_{3-4}} \overline{OPENDAYS}_{s_{3-4},t} \\ & + \epsilon_{st}, \end{aligned} \tag{4}$$

where $OPENDAYS_{st}$ denotes the number of days agent s keeps the shop open in month t, $\overline{OPENDAYS}_{s_{d_1-d_2}t}$ denotes the average number of days other agents who are within between d_1 and d_2 kilometers from agent s keep the shop open in month t, $UPTK_{st}$ denotes uptake of grains at agent s in month t, α_s denotes agent fixed effects that capture aspects such as shop location and shop size that are likely to impact the number of days the shop is kept open and the uptake, β_t denotes time fixed effects that captures seasonal patterns in uptake, and $\gamma_{s_{0-1}}$ to $\gamma_{s_{3-4}}$ are the associations of interest.

Results of this estimation, shown in Table 5, reveal three major observations. First, a one-day increase in the number of shop open days of the focal agent is associated with an increase in an uptake of 108 kg. Second, the uptake at the focal agent is negatively associated

Table 5. Association Between Uptake at an Agent and the Number of Days Neighboring Agents Keep Their Shops Open

Association of uptake at an agent with average shop open days of	(1) $UPTK_{st}$
Focal agent (γ_0)	108.063*** (2.213)
Agents between 0 and 1 km ($\gamma_{s_{0-1}}$)	−32.639*** (3.109)
Agents between 1 and 2 km ($\gamma_{s_{1-2}}$)	−17.554*** (3.134)
Agents between 2 and 3 km ($\gamma_{s_{2-3}}$)	−5.083 (3.581)
Agents between 3 and 4 km ($\gamma_{s_{3-4}}$)	−8.662** (3.882)
Number of agents	12,257
Number of observations	70,109

Notes. Column (1) shows the results from estimating (4) with the dependent variable as uptake at an agent on an agent-month panel collected from AP (our control state) between March 2018 and August 2018. The term ϵ_{st} is clustered at the agent level.
$^{**}p < 0.05$; $^{***}p < 0.01$.

with the number of shop open days of the neighboring agents. Specifically, a one-day increase in the average number of shop open days of other agents within 1 km is associated with a 32 kg decrease in the uptake at the focal agent. Considering the average daily uptake of 557 kg at an agent (the ratio of average monthly uptake over the average number of days an agent keeps the shop open), this translates to a 5.8% decrease in an agent's uptake. Third, we find that a one-day increase in the average number of shop open days of other agents within a 1 to 2 km radius is associated with a 3.1% increase in an agent's uptake per day. These results suggest that beneficiaries exercise their agency in choosing to collect grain from agents that keep their shops open for a larger number of days, and distance is an important determinant of the agent they choose to collect their grain from.

We obtain similar results from an alternate ordinal specification where we estimate the association between uptake at the agent and the number of days the *n*th nearest agent keeps the shop open. We present the estimation details and results in the Online Appendix, Section A.5.1.

Number of Shop Open Days of an Agent and the Neighboring Agents. In the absence of choice, we expect each agent to choose the number of days to keep the shop open independently, as they cater to different sets of preassigned beneficiaries. However, if choice induces a threat of losing beneficiaries to other agents who keep their shops open longer, we expect an agent to respond by keeping the shop open for more days, leading to a positive association. Moreover, given that the beneficiaries are less likely to use an agent that is farther away, we expect the strength of this association to decrease as the distance between the focal agent and the neighboring agent increases.

We use a Poisson regression specification on the shop open days data set using the following log-linear function:

$$\begin{aligned}\log(OPENDAYS_{st}) = \alpha'_s + \beta'_t + \gamma'_0 OPENDAYS_{s,t-1} \\ + \gamma'_{s_{0-1}}\overline{OPENDAYS}_{s_{0-1},t-1} \\ + \gamma'_{s_{1-2}}\overline{OPENDAYS}_{s_{1-2},t-1} \\ + \gamma'_{s_{2-3}}\overline{OPENDAYS}_{s_{2-3},t-1} \\ + \gamma'_{s_{3-4}}\overline{OPENDAYS}_{s_{3-4},t-1} + \epsilon'_{st},\end{aligned} \tag{5}$$

where α'_s denotes agent fixed effects, and β'_t denotes month fixed effects. We include month- and agent-level fixed effects to capture aspects such as seasonal patterns, shop location, and shop size that are likely to impact the number of days the shop is kept open. We also include the number of days the shop is kept open in the previous month ($OPENDAYS_{s,t-1}$) to account for potential autoregressive effects. The coefficients of interest are $\gamma'_{s_{0-1}}$ to $\gamma'_{s_{3-4}}$.

We make two observations from the results of this estimation shown in column (1) of Table 6. First, the

Table 6. Association Between the Number of Days an Agent Keeps the Shop Open and the Number of Days Neighboring Agents Kept Their Shops Open in the Previous Month

Association of the average shop open days of an agent with lagged shop open days of	(1) $OPENDAYS_{st}$
Focal agent (γ'_0)	0.059*** (0.0006)
Agents between 0 and 1 km ($\gamma'_{s_{0-1}}$)	0.007*** (0.0005)
Agents between 1 and 2 km ($\gamma'_{s_{1-2}}$)	0.003*** (0.0004)
Agents between 2 and 3 km ($\gamma'_{s_{2-3}}$)	0.004*** (0.0005)
Agents between 3 and 4 km ($\gamma'_{s_{3-4}}$)	0.004*** (0.0005)
Number of agents	12,231
Number of observations	58,665

Notes. Column (1) shows the results from estimating (4) with dependent variable as the shop open days of an agent using an agent-month panel collected from AP (our control state) between March 2018 and August 2018. The term ϵ'_{st} is clustered at an agent level.
$^{***}p < 0.01$.

number of shop open days of the focal agent is positively associated with the lagged number of shop open days of other agents in the vicinity. Specifically, a one-day increase in the average number of open days within 1 km results in a $0.70\%((e^{\gamma_{s_{0-1}}}-1)*100)$ increase in the expected number of shop open days of the focal agent. Considering the average number of shop open days as 12.6 days from Table A.7 in the Online Appendix, this translates to an increase of 0.088 days. Second, the strength of association drops to $\sim 0.30\%((e^{\gamma_{s_{1-2}}}-1)*100)$ for distances greater than 1 km. The drop suggests that shops that are farther away have lesser influence on the number of days the focal agent keeps the shop open in a month. We obtain similar results from an alternate ordinal specification where we estimate the association between the number of days the focal agent chooses to keep the shop open and the number of days the *n*th nearest agent keeps the shop open (see the Online Appendix, Section A.5.2, for details).

Collectively, associations in Tables 5 and 6 and their decreasing trends with distance suggest that agents may have responded to choice by increasing the number of days they keep their shops open in anticipation of losing beneficiaries to other agents in the vicinity. That is, choice may have played a self-monitoring role in changing agent behavior. Other explanations for change in agent behavior such as increased monitoring, although plausible, cannot be explicitly tested using available data.

6. Threats to Identification

In this section, we conduct three sets of analyses to verify that our results are unlikely to be driven by observed/unobserved confounding factors: testing for parallel trends, matching, and temporal proximity with digitalization.

6.1. Parallel Trends

We test for parallel trends using an event study specification where CHC_{it} is interacted with indicator variables created for each time period. Event-study specification for conventional DID settings includes interacting the treatment indicator variable with time dummies for pretreatment periods. Each coefficient is interpreted as the difference between the treatment and control groups in that time period relative to a chosen base time period. Consequently, if the magnitudes of the interaction coefficients are ≈0, or statistically insignificant, we conclude that the identification condition of the parallel trends assumption is satisfied, conditional on all other covariates in the model (Callaway and Sant'Anna 2021, Braghieri et al. 2022, Dee et al. 2023, Roth et al. 2023).

However, in a reverse DID setting, the treatment and control are comparable *after* the intervention, and therefore, the test for parallel trends must be conducted after the intervention. Accordingly, in our study setting, we test whether treatment and control move in parallel after the 15th month, that is, when agent choice is introduced in both states, and check for statistical significance of the coefficients obtained from interacting the treatment indicator with time dummies for *posttreatment periods*. Each posttreatment interaction coefficient is interpreted as the difference between the treatment and control groups in that time period relative to the first period. Hence, the stabilization of posttreatment coefficients around a constant value, after few initial posttreatment periods, would imply that the assumption of parallel trends holds in a reverse DID setting in *posttreatment periods*. We present a detailed discussion of the verification of parallel trends in the Online Appendix, Section A.6, which includes results of the event study specification, sensitivity analysis proposed by Rambachan and Roth (2023), and a falsification check. We find that the parallel trends assumption is reasonably satisfied in our study setting.

6.2. Matching

Despite being a unified state for several years, there is a possibility that subdistricts in AP and TS are not truly comparable because of unobserved aspects such as beneficiaries' dependency on the food security program and varying state capacity to execute the program. In such a case, the effect size in our model may be capturing these differences and not the impact of agent choice itself. We address this question by using two approaches to match subdistricts in both states and evaluate the impact of agent choice on the matched sample.

6.2.1. Proximity-Based Matching. In this approach, we use data from only those subdistricts that lie along the state boundary separating AP and TS in our estimation (Chagas et al. 2012, Abbay and Rutten 2016). Given the geographic proximity of these subdistricts, it is reasonable to believe that they are similar in almost every aspect, and the only reason subdistricts in TS did not have agent choice until April 2018 is because of an exogenous decision that divided the unified state into separate states in 2014.

Results of estimating (1) on this matched subsample are shown in column (2) of Table 7. We find that the impact of agent choice in border subdistricts continues to be positive and statistically significant. Interestingly, it is nearly double the effect size estimated from our main model (39,239 vis-á-vis 20,273 kg). We conjecture that this may be due to migration of agricultural labor from TS into AP, which has been reported in prior ethnographic studies (Deshingkar and Akter 2009, Keshri and Bhagat 2010). Before the introduction of choice, such migrating households would have had to let go of

Table 7. Exogeneity of Intervention

	(1) Base model	(2) Proximity	(3) NNM	(4) CM	(5) IPWs
Impact of agent choice (δ)	20,273***	39,239***	20,629***	20,431***	21,660***
	(1,975)	(7,204)	(1,785)	(1,735)	(2,773)
Impact of quantity allocated (θ_1)	0.94***	0.96***	0.94***	0.94***	0.96***
	(0.01)	(0.02)	(0.01)	(0.01)	(0.02)
Impact of strike (θ_2)	−11,362.66***	−28,350***	−13,251***	−13,370***	−14,349***
	(1,349.59)	(7,019)	(1,446)	(1,442)	(2,457)
Adjusted R^2	0.898	0.97	0.90	0.93	0.94
Observations	28,232	1,187	24,900	23,907	27,644

Notes. Results shown are for subdistrict-month panel regressions with subdistrict and month fixed effects, state time dummies, and standard errors clustered at the subdistrict level. Column (1) shows the base model (results from estimating (1) with the dependent variable *Uptake*). Column (2) shows the results from estimating (1) with the dependent variable *Uptake* for a subsample including only bordering districts. Column (3) shows the results from estimating (1) with the dependent variable *Uptake* by using nearest neighbor matching (NNM) using night-light data. Column (4) shows the results from estimating (1) with the dependent variable *Uptake* by using caliper matching (CM) using night-light data. Column (5) shows the results from estimating (1) with the dependent variable *Uptake* by using inverse probability weights (IPWs) using night-light data.

***$p < 0.01$.

their grain entitlements in TS because of large distances between their original residence (where the preassigned agent is located) and place of work. However, with the introduction of choice, they have an option of visiting an agent in TS nearest to their place of work, that is, near the interstate border, to collect their entitlements and go back to their place of work. With cost savings of INR 25 per kilogram of grain, exercising this option may turn out to be cheaper than buying grain from the open market, despite the additional transportation costs.[11]

6.2.2. Development-Based Matching. In this approach, we match subdistricts in AP and TS with similar levels of economic development. We conjecture that regions with similar levels of economic development are likely to be similar in terms of confounding factors such as beneficiaries' dependency on subsidized grain, quality of network connectivity (required for biometric devices to access the central database for verification), and the agents' capability to perform digital transactions.

Following Henderson et al. (2012), we use the mean value of radiance in the night-light data from each subdistrict as a proxy for economic development (see the Online Appendix, Section A.7, for a detailed data description). We compute this measure in the month of April 2019, that is, after the introduction of agent choice and at the end of our study period, in line with the reverse DID framework where treatment and control are comparable after the introduction of the intervention.

We compute the propensity of a subdistrict obtaining agent choice based on the mean value of radiance and use these propensity scores to reestimate (1) using three well-known approaches: nearest neighbor, caliper, and inverse propensity weight matching (see the Online Appendix, Section A.7, for more details of the matching procedures). Results of these estimations, shown in columns (3), (4), and (5) of Table 7, are similar to those in our main model. We reestimate (1) using the proportion of allocated grains collected as a dependent variable. Results are shown in Table A.13 in the Online Appendix and are consistent with our findings in Table 7.

Last, we show that our matching procedures improve the comparability of the treatment and control groups by measuring standardized differences among both the groups before and after matching (see Table A.14 in the Online Appendix for details).

6.3. Confounding Effect due to Temporal Proximity with Digitization

In both AP and TS, the introduction of agent choice closely followed the installation of biometric authentication devices. In TS, our treatment state, the gap between the two interventions is as low as a month for some subdistricts (see Figure A.6 in the Online Appendix). The installation of biometric devices alone, without the provision of choice, is known to decrease the recorded uptake because of reduced diversion of grains into the open market (Muralidharan et al. 2020, Ganesh et al. 2019). Thus, it is possible that the observed effect size in our main model (20,273 kg) is a combined effect of both the installation of biometric devices and agent choice. In this section, we study whether our estimated effect size varies because of the temporally proximate intervention of the installation of biometric authentication devices.

We reestimate the model including only those subdistricts in which all agents were provided with biometric devices at least four months before the introduction of

Table 8. Provision of Biometric Devices

	(1) Base model	(2) Subdistricts digitized before January 2018	(3) Subdistricts digitized before January 2018 (IPW)
Impact of agent choice (δ)	20,273***	17,968***	19,503***
	(1,975)	(2,147)	(2,807)
Impact of quantity allocated (θ_1)	0.94***	0.94***	0.96***
	(0.01)	(0.01)	(0.02)
Impact of strike (θ_2)	−11,362.66***	−9,737***	−12,901***
	(1,349.59)	(1,439)	(2,464)
Adjusted R^2	0.898	0.90	0.94
Observations	28,232	25,264	24,676

Notes. Results shown are for subdistrict-month panel regressions with subdistrict and month fixed effects, state time dummies, and standard errors clustered at the subdistrict level. Column (1) shows the base model (results from estimating (1) with the dependent variable *Uptake*). Column (2) shows the results from estimating (1) with the dependent variable *Uptake* for a subsample in which all agents were provided biometric devices at least four months before the introduction of choice. Column (3) shows the results from estimating (1) with the dependent variable *Uptake* for a subsample in which all agents were provided biometric devices at least four months before the introduction of choice and by using inverse probability weights (IPWs) using night-light data.

$^{***}p < 0.01$.

agent choice in April 2018, as the time gap between digitization and agent choice potentially alleviates interference between the two treatments in this subsample. The resulting subsample includes 331 out of 572 subdistricts in TS (our treatment) and all 659 subdistricts from AP (our control). Results of this estimation shown in column (2) of Table 8 indicate that agent choice continues to have a positive and significant impact on uptake that is comparable in magnitude to the estimate obtained from our main model (17,968 kg vis-á-vis 20,273 kg, $p = 0.283$[12]).

Furthermore, it is possible that TS may have prioritized provision of biometric devices to subdistricts that are closer to administrative centers and with better digital infrastructure such as internet and telephone connectivity. Given that better digital infrastructure and proximity to administrative centers is likely to be correlated with economic development, we again use night-light data (Henderson et al. 2012) to construct a more appropriate control group for the 331 chosen subdistricts from TS and reestimate our model on this subsample of TS subdistricts using inverse propensity weighting. Results of this estimation in column (3) of Table 8 show that the effect size is comparable to our estimate from the main model (19,503 kg per subdistrict per month vis-á-vis 20,273 kg). Our findings are robust to alternate matching methods such as nearest neighbor and caliper matching (see results in Table A.15 in the Online Appendix).

7. Discussion and Managerial Implications

Using a natural experiment between two neighboring states in India, we find that the provision of technology-enabled agent choice enables more beneficiaries to collect their entitlements from the program. Nearly all of the increase is attributable to new beneficiaries collecting their entitlements from their originally assigned agents. We find associative evidence to suggest that agents may have responded to choice with improved adherence to stipulated operating guidelines in anticipation of losing their preassigned beneficiaries and associated compensation to other agents in the vicinity.

Our results focus on the impact of agent choice in improving access to food grains for additional beneficiaries and leave out other dimensions through which agent choice may have impacted beneficiary welfare. To begin with, our analysis does not capture the impact of agent choice on the actual quantity of food grains received by the beneficiaries (Section 5.2). Next, our analysis also does not study whether utilization of choice is welfare enhancing. About 2,103 beneficiaries in each subdistrict-month are choice users and constitute about 17% of 12,323 beneficiaries per subdistrict. On the one hand, use of an alternate agent could result in higher welfare for choice users, if the alternate agent is easily accessible through public transport (Rajan et al. 2016) or available when there is disruption in service at the preassigned agent for reasons such as power outage, network failure, etc. On the other hand, some beneficiaries may be forced to use an alternate agent, even when the preassigned agent is the preferred agent, due to reasons such as stockouts.

Nonetheless, we believe that our results inform the ongoing debate on cash versus kind in delivering social assistance programs. Governments in developing countries that operate in-kind transfers of commodities similar to India's PDS are piloting interventions to completely replace physical distributions of commodities (in-kind transfers) with cash transfers. The primary justification for cash transfers is that they allow beneficiaries to buy whatever they want from wherever they want (for examples from food security programs from Bangladesh, Ecuador, Eqypt and Sri Lanka, see Gentilini and Omamo 2011, Gentilini et al. 2014, Tilakaratna and Sooriyamudali 2017; for examples from cooking gas and fertilizer transfer programs from India, Indonesia, and Nigeria, see Kishore et al. 2021, Kuehl 2021, Perera et al. 2021, Mukherjee et al. 2023).

However, there is no clear consensus yet on whether cash transfers outperform in-kind transfers in achieving the desired policy outcomes (for a detailed review in food security programs, see Gentilini 2016; for a review in energy subsidy programs, see Mukherjee et al. 2023). Studies across several countries report beneficiaries expressing preference for transfers of commodities over cash for reasons such as the potential misuse of cash (Currie and Gahvari 2008, Sabates-Wheeler and Devereux 2010, Pingali et al. 2019, Torkelson 2020), and, finally, implementing cash transfers is challenging, as the magnitude of the cash transfers needs to be periodically adjusted based on the volatility of commodity prices in the local markets (Currie and Gahvari 2008, Beatty et al. 2009, Sabates-Wheeler and Devereux 2010, Pingali et al. 2019). Our results indicate that alternate designs of providing choice even in a limited form, that is, choice in the place where the beneficiaries can collect their entitlements, with products and their prices being fixed by the government, has a welfare-enhancing impact without a significant disruption to the underlying operational aspects of the program.

Finally, our study setting highlights the importance of studying operating model innovations for executing public programs at the BoP. Recent work in operations management literature has studied various aspects of operations at the BoP, such as inventory replenishment, after sales service, multichannel delivery, and so on (Acimovic et al. 2018, Calmon et al. 2022, Gui et al. 2019, Uppari et al. 2019, Plambeck and Ramdas 2020, Ramdas and Sungu 2024). However, they focus on private players where financial profitability (or feasibility for not-for-profit organizations) is one of the primary objectives. Given that public programs aim to achieve a policy mission such as the right to food, with financial aspects typically playing the second fiddle, we believe the nature of innovations in these contexts will be different and can be a promising avenue for further research.

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Endnotes

[1] The administrative hierarchy in the order of increasing granularity is as follows: centre, state, district, subdistrict.

[2] Similar technology-based monitoring mechanisms have been effectively used in private sector contexts to improve compliance of frontline workers. For instance, Staats et al. (2017) show that introducing electronic monitoring increases compliance to hand hygiene protocols among healthcare workers. Pierce et al. (2015) show that installing theft detecting software in point-of-sale devices at restaurants decreases instances of server misconduct.

[3] Magnitude of entitlement varies based on the economic status of a household, which is identified either as Antyodaya Anna Yojana (AAY) or priority household (PHH), with the former being the poorest of the poor. AAY households receive an entitlement of 35 kg per household irrespective of the number of individuals in the household, whereas PHH households receive an entitlement of 5 kg per person per household up to four persons per household.

[4] The market price is obtained from the Agmarknet portal, https://agmarknet.gov.in/.

[5] The wage details are obtained from the Mahatma Gandhi National Rural Employment Guarantee Act portal, https://www.im4change.org/news-alerts/no-change-in-mgnrega-wage-rates-observed-between-2018-19-and-2019-20-for-4-states-2-uts-4686997.html.

[6] A potential approach to test for parallel trends could have been to observe TS and AP for a long enough duration for TS to reach a steady state. However, such long observation windows are often characterized by the presence of other interventions like policy changes, elections, other technological interventions, and so on. For instance, in our context, the government of India started piloting pan-India agent choice in small pockets of AP and TS from July 2019, allowing beneficiaries from TS to collect grains from AP and vice versa. This means uptake in TS (or AP) can no longer be attributed to beneficiaries within the state, thereby posing a threat to our identification strategy if we had extended the observation window.

[7] This behavior has also been reported from other states, such as Jharkhand, that are not a part of our study setting (Scroll 2022).

[8] The average entitlement per beneficiary in Telangana is obtained from https://www.civilsupplies.telangana.gov.in/Annual%20Report%202019%20New.pdf.

[9] We also estimate the model with DEN_i as a continuous variable and our results are consistent. See the results in column (2) of Table A.5 in the Online Appendix. The distribution of DEN_i is shown in Figure A.1 in the Online Appendix.

[10] Typically, one agent is assigned for every 1,000 beneficiaries.

[11] Similar reports of policy differences across borders driving sales in regions adjacent to the border have been documented in the contexts of alcohol taxation (Beatty et al. 2009) and marijuana prohibition (Hansen et al. 2020).

[12] The p-value is obtained by comparing the means of the estimates 20,273 kg and 17,968 kg in columns (1) and (2) of Table 8 using a t-test with the squares of corresponding standard errors as variances.

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