Choice based reforms in delivering food security: Analysis of an intervention from the Indian Public Distribution System (PDS)

Maya Ganesh* Rakesh Allu† Sarang Deo* Sripad Devalkar*

maya_ganesh@isb.edu aa2688@cornell.edu sarang_deo@isb.edu sripad_devalkar@isb.edu

Abstract

Achieving 'Zero Hunger' by 2030 is a global priority. Government-managed food security programs are a major instrument for achieving this goal, particularly among developing countries. Despite the vast amount of resources spent on these programs, they suffer from several inefficiencies largely attributable to the monopoly of agents involved in last-mile delivery. Governments have attempted to address these inefficiencies by either privatizing these programs or replacing them with cash transfers which allow beneficiaries to use cash as they deem most appropriate. However, evidence on the relative effectiveness of these approaches is mixed. In this paper, we describe an alternate approach called *portability* which has been introduced in the Indian Public Distribution System (PDS). Portability offers beneficiaries the choice of *when* and *where* they can avail of their food entitlements while the government controls *what* and *how much*. We use detailed and large-scale program data from one Indian state to analyze the uptake of portability among beneficiaries and identify its underlying drivers. We find that a sizeable fraction (~28%) of beneficiaries utilize this choice despite its limited form. Primary factors influencing the uptake are the number of agents a beneficiary has access to and the number of days in a month an agent is open to distributing food entitlements. We find that usage levels among the vulnerable populations such as the rural, the poor, the elderly and the socially disadvantaged, to be ~24%, ~29%, ~24% and ~16% lesser in comparison to their non-vulnerable counterparts respectively.

Keywords: Portability, Public Distribution System, Cash Vs In-Kind transfers, food security programs, choice in public services

* Indian School of Business, Hyderabad, India

† Cornell University Samuel Curtis Johnson Graduate School of Management, Ithaca, New York, United States

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1. **Introduction**

In many developing countries, government-managed food security programs are a major policy instrument in achieving the Sustainable Development Goal of 'Zero hunger.' As of 2019, approximately 92% of the low-income and 73% of the low- and middle-income countries had some form of food distribution program (Gentilini, Honorati, & Yemtsov, 2014). Despite substantial budgetary allocations (typically about 1% of the national GDP), many programs have not made satisfactory progress toward the 'Zero Hunger' goal (FAPDA, 2019). Most common problems afflicting these programs include leakage of grains to open markets, poor quality of grains and apathetic customer service. A key structural determinant of these problems is the involvement of monopolistic government agents, who do not have strong incentives to improve efficiency and customer service (Banerjee, Hanna, Kyle, Olken, & Sumarto, 2017; Pingali, Mittra, & Rahman, 2017; The World Bank, 2003).

Several supply- and demand-side interventions have been implemented recently to overcome this barrier and improve program efficiency. For instance, on the supply-side, privatizing the last mile delivery of grains in Indonesia's food security program *(Raskin)* through a competitive bidding process enabled the entry of new players, which further reduced operational cost without compromising the quality of delivery (Banerjee et al., 2017). On the demand-side, the government of Sri Lanka integrated its food security program with its national poverty alleviation program (*Samrudhi*) by replacing in-kind food transfers with cash transfers to reduce fiscal costs (Tilakaratna & Sooriyamudali, 2017). Several other countries such as Bangladesh, Egypt and Ecuador are actively piloting various designs for providing cash in place of in-kind transfers to their beneficiaries (Gentilini, 2007; Gentilini & Omamo, 2011; Gentilini et al., 2014). Proponents of this solution argue that cash provides beneficiaries with the freedom to purchase *whatever* they want, *whenever* they want, and from *whomever* they want while simultaneously reducing the government's cost of program delivery (del Ninno, Dorosh, & Subbarao, 2007; Hidrobo, Hoddinott, Peterman, Margolies, & Moreira, 2014; Lusk & Weaver, 2017). However, detractors argue that cash transfers may not be effective in eliminating hunger if: (i) beneficiaries willingly use cash for non-food purchases (e.g., alcohol or tobacco), or (ii) beneficiaries face barriers in using cash for food purchases due to inaccessibility of markets or high volatility in prices, and (iii) magnitude of cash transfer is not periodically adjusted to the volatility of food prices in the local markets (Paul & Savage, 2006; Currie & Gahvari, 2008; Sabates-Wheeler & Devereux, 2010; Demirguc-Kunt, 2012; Michelson et al., 2012; Khera, 2014; Pradhan, Roy, & Sonkar, 2015; Lentz, Ouma, & Mude, 2016; Tilakaratna & Sooriyamudali, 2017; Pingali, Aiyar, Abraham, & Rahman, 2019).

Recently, several Indian states have implemented a novel intervention called "Portability" in their food security program, which incorporated some advantages of privatization and cash transfers while mitigating some of their disadvantages.[i] Under this intervention, beneficiaries can claim their entitlement of subsidized food grains from any licensed shop within the state instead of a single pre-assigned shop.[ii] It aims to reduce monopolistic power of the shop dealers, induce competition among them and improve their quality of service by providing the beneficiaries the choice of '*where*' to avail of their entitlements without changing '*what*' and *'how much'* they purchase (R. Ali, 2018; The Hindu, 2018, 2019). However, arguments based on stakeholder theory and agency theory suggest that lack of adequate financial incentives for shop dealers and the governments' inability to actively monitor their behavior may not foster adequate competition among them, thereby casting a shadow on the effectiveness of the intervention (Sharma & Gupta, 2017). Empirical evidence regarding the impact of this intervention is limited in its geographic scope (restricted to urban areas of one state), relies mostly on descriptive statistics, and is mixed. One study found that beneficiaries prefer to use shops with better service quality and road connectivity (Rajan, Chopra, Somasekhar, & Laux, 2016) whereas another found that the fraction of beneficiaries utilizing portability dropped to almost zero within 18 months after the launch of the intervention (Joshi, Sinha, & Patnaik, 2016).

In this paper, we contribute to this discussion by analyzing large-scale program data on the implementation of portability across the entire state of Andhra Pradesh over a period of six months (March 2018 to August 2018). We measure utilization of portability by beneficiaries, characterize its temporal and spatial heterogeneity, and estimate regression models to identify association of portability utilization with characteristics of beneficiary households and program administration. Given that the Government of India is envisioning a national level rollout of this program (India Today, 2019), our findings can be used as inputs both during design as well as execution of such rollout. More broadly, our study contributes to the sizeable literature on choice-based interventions in public programs such as healthcare, pensions and insurance (Fotaki & Boyd, 2005; Fischer, González, & Serra, 2006; Le Grand, 2007; Clarke, Newman, & Westmarland, 2008). However, their findings may not be directly applicable to food security programs due to limited role of competitive levers such as product differentiation and service.

The remainder of the article is structured as follows. We provide an overview of the Indian food security program in Section 2. In Section 3, we describe our data, present our measures of portability utilization and various factors that may be associated with it. Section 4 describes the temporal and spatial patterns of portability utilization observed in the data. We analyze the influence of different factors on the usage of portability and conduct robustness checks in Sections 5. We conclude by discussing our results and their policy implications in Section 7.

2. Background: Indian Public Distribution System

India's Public Distribution System (PDS) is one of largest food security programs in the world. In 2018, it spent roughly 1% of the national GDP (₹1.15 Trillion) to provide food grains to around 160 million households. Each household, based on its economic status, is entitled to receive a fixed quantity of food grains every month through government licensed outlets called Fair Price Shops (FPSs) at heavily subsidized prices (₹1/Kg compared to market prices of ₹28 - ₹40/Kg)[iii]. Typically, private dealers or cooperative societies are issued a license to manage the FPS for a fixed period of 3 years and are paid a commission of about ₹0.70 per Kg of grains distributed to beneficiaries[iv].

Traditionally, each FPS dealer received a paper-based roster of beneficiaries and issued grains to beneficiaries only after verifying their names in a government issued identity card. This system accorded monopoly power to the FPS dealers over beneficiaries, which in turn led to inefficient and poor quality of service manifesting in terms of frequent FPS closures, mistreatment of beneficiaries, long queues, adulteration of grains, overcharging / underweighting (Khera, 2011; Vaidya & Somasekhar, 2013; Sargar, Kumar, Nakade, & Borkar, 2014; Dreze & Khera, 2015; Sati, 2015; Sharma & Gupta, 2017). Despite the presence of grievance redressal mechanisms and vigilance committees, only an estimated 1.5% of the beneficiaries across the country were aware of them (NCAER, 2015).

Beginning in 2010, central and several state governments have embarked on an ambitious plan of end-to-end digitization of the PDS. A prominent feature of this initiative is the use of biometric authentication of beneficiaries by installing electronic devices at FPSs that are linked to central servers (Allu, Deo, & Devalkar, 2019). As of September 2019, around 10 states have started to leverage this feature to allow beneficiaries to authenticate their identity and collect their entitlements at any FPS in their state (R. Ali, 2018; India Today, 2019). It is expected that such "portability" of benefits will provide convenience to the beneficiaries and cut down the monopoly power of the FPS dealers.

3. Data and Measures

3.1 Data

Our study is based in Andhra Pradesh, which was the first Indian state to introduce state-wide portability in 2015. We collected publicly available program data for a period of six months (March 2018 to August 2018) from a state government website operated by The Department of Consumer Affairs, Food and Civil Supplies (https://aepos.ap.gov.in/ePos/). It comprises 75.57 million transactions made by 13.92 million households at 29,212 FPSs spread over 13 districts and 664 sub-districts and is organized into three parts—beneficiary dataset, FPS dataset and transaction dataset, which we describe below.

3.1.1 Beneficiary Dataset

The beneficiary dataset contains the following information on each beneficiary household: a unique identification number, name of the FPS that it was originally allocated to (hereafter "home shop"), district/sub-district of residence, gender and name of the head of the household, its economic status captured by categories defined in the National Food Security Act—Priority Households (PHH) or Antyodaya Anna Yojana (AAY) households, where the latter comprises poorer households[v].

3.1.2 Fair Price Shop (FPS) Dataset

The *FPS dataset* contains the following information for each shop: a unique identification number, its geographic coordinates (latitude and longitude), address and dealer's name[vi].

We classify each shop as a cooperative society if the dealer name contains specific key words, e.g., Self-Help Group (SHG), Co-operative, Society, and the rest as private[vii]. For all shops identified as privately owned, we predict the gender of the dealer from their name using Naïve Bayes Classifier algorithm (Langley, Iba, & Thompson, 1992; Friedman, Geiger, & Goldszmidt, 1997), which we train using the name and gender of household members from the beneficiary dataset[viii].

We categorize the location of a shop (urban/town/rural) by extracting the specific village name/city name from its address and mapping it to the village amenities, towns amenities and urban agglomerations datasets of the 2011 Census of India.[ix,x]

3.1.3 Transaction Dataset

Each transaction in the transaction dataset is identified by a unique transaction ID and contains the unique identification codes of the beneficiary household and the shop, date of the transaction, and quantities of the different commodities purchased. For computational ease, we draw a simple random sample of 500,000 beneficiary households analyzed over a period of six months [xi] [xii].

3.2 Measures

3.2.1 Portability Utilization

Our main outcome variable is the utilization of portability at the household-month level, which we denote using an indicator variable, *Portability Usage*$_{it}$. For a transaction involving household i in month t in the *transaction dataset*, we compare the home shop of the household obtained from the *beneficiary dataset* with the shop involved in the transaction. The household is identified as having used portability *Portability Usage*$_{it}$ = 1) if the two are different and not (*Portability Usage*$_{it}$ = 0), otherwise.

3.2.2 Factors affecting portability utilization

We posit that a household's utilization of portability is influenced by two categories of factors: (i) those related to the quality of the service and the operation of shops in the PDS, which we call as PDS Characteristics (PDSC), and (iii) those related to the sociodemographic characteristics of the households themselves, which we call as household characteristics (HHC).

PDS Characteristics

We consider two categories of variables relevant to the Public Distribution System (PDS)—first belonging to the home shop, i.e., the shops to which households were assigned before the introduction of portability and the second belonging to the network of shops other than the home shop.

We hypothesize that households whose home shops are open for a fewer days in a given month would have a higher necessity to search for alternate shops. We define '*FPS_open_days*$_{it}$' as the number of days in which we observe at least one transaction at the home shop of household *i* in month *t*.[xiii] Existing literature on PDS has shown that mistreatment by shop dealers, particularly by male dealers towards women beneficiaries, is a pressing concern among the households (Vaidya & Somasekhar, 2013). Given that women take the primary responsibility of collecting grains in most households (Sharma & Gupta, 2017; Pradhan & Rao, 2018), we hypothesize that households assigned to shops managed by men are more likely to use portability in search of safer alternatives[xiv]. Further, Nagavarapu et al. (2016) find that shops operated by cooperatives/self-help groups are more likely to be monitored closely by the community and hence are likely to be more beneficiary centric than those managed by private dealers. Therefore, we hypothesize households whose home shops are managed by cooperatives/self-help groups are less likely to use portability. To capture these effects, we define '*dealership*$_i$' as a categorical variable which takes one of the three values—co-operative managed, privately managed by a male or privately managed by a female dealer.

As the home shop of a household is typically the one closest to it, using a foreign shop may lead to additional cost in terms of time and money. Hence, we hypothesize that, all else being equal, the likelihood of a household using portability is higher if the number of alternative shops in its vicinity is higher. We define '$FPS\_density\ (x\ km)_i$' as the number of shops within *x* km from a household *i*'s home shop[xv].

Household Characteristics

We use four dimensions of household vulnerability—economic, physiological, geographical and social—which may affect their need for as well as actual usage of portability. Controlling for PDS characteristics, economically vulnerable households are more likely to need portability because of their higher dependence on PDS for food security. However, these households are also less likely to have the financial resources and/or time to afford using an alternate shop. Thus, the net impact of economic vulnerability on usage of portability is unclear. We use the information on economic category of households from the *beneficiary dataset* to define a binary variable 'AAY_i', which takes a value 1 if it belongs to the AAY category, and 0 if it belongs to PHH category.

A household consisting of elderly members is less likely to use portability because of their inability to travel and carry grains over longer distances. To capture physiological vulnerability, we construct an indicator variable, '$Elderly_i$', which takes the value of 1 if all its members are above the age of 60 years and 0 if at least one member is below the age of 60 years.

Households belonging to certain socially vulnerable groups such as Scheduled Castes (SC), Scheduled Tribes (ST) and other Primitive Tribal Groups (PTG) face discrimination in accessing government schemes including PDS entitlements (Jan Sahas, 2009; Thorat & Newman, 2010; Sabharwal, 2011; Nagavarapu & Sekhri, 2016; Pradhan & Rao, 2018). These households are also typically not well versed with digital media and hence are less likely to access information regarding stock availability at each shop, shop opening times, and address of nearest shop that is posted by the government and is useful while choosing an alternate shop to utilize portability[xvi] (Kumar & Best, 2007; J. Ali & Kumar, 2011). We do not have access to data on caste at the household level. Hence, we use Socio-Economic Caste Census (SECC) data published in the year 2014 to define socially vulnerable sub-districts as those with proportion of population belonging to socially vulnerable groups being above the 75th percentile across all sub-districts in the country.[xvii] We then define a binary variable '*SC/ST/PTG*$_i$' which takes a value 1 if household *i* resides in a socially vulnerable sub-district and 0 otherwise.

Households in urban areas are more likely to have easier access to cheaper transport facilities compared to those in smaller towns and rural locations. Similarly, urban households may experience more frequent need to use portability due to change in residential location or availability of alternate shops closer to their work locations. To capture this, we define a categorical variable, '*Location*$_i$', for each household that takes one of three values – urban, town, or village. As a beneficiary household's address is not observed, we use the location of the household's home shop as a proxy because typically the home shop is the FPS that is closest to the household.

Table 1 shows the descriptive statistics related to the different factors described above. We find that shops were open for an average of 12.23 days per month compared to the specified operational guideline of 15 days (see **Table A1**Table A1 in the appendix for percentage of shops open by day of the month). Slightly more than 2.5% household-month combinations corresponded to a household's home shop being closed. Home shop of 5.24% households was managed by cooperatives or self-help groups, of 48.29% households was managed by private male dealers whereas that of the rest was managed by private female dealers. On average, each household had about 3 other shops within 0.5 km from its home shop whereas about 27% households did not have another shop within 1 km of their home shop. Also, 6.39% households had only elderly beneficiaries, 6.24% households belonged to AAY category, 11.82% households were located in sub-districts with large SC/ST/PTG population and 79.27% were located in rural areas. (see Table A2Table A2 in appendix for correlation between various factors).

Table 1: Descriptive statistics of factors affecting portability utilization

	Proportion (SD)	Mean (SD)
PDS characteristics (PDSC)		
FPS open days	-	12.23 (3.98)
Dealership		
– Co-operative	0.05 (0.0003)	
– Private male	0.48 (0.0007)	
– Private female	0.46 (0.0007)	
FPS density (0.5 km)	-	3.91 (3.46)
FPS density (0.5km - 1.0 km)	-	5.89 (8.20)
FPS density (1.0km - 2.0 km)	-	12.21 (18.80)
Household characteristics (HHC)		
AAY	0.06 (0.0003)	-
SC/ST/PTG	0.12 (0.0004)	-
Elderly	0.06 (0.0003)	-
Location		
– Rural	0.79 (0.0005)	
– Town	0.11 (0.0004)	
– Urban	0.09 (0.0004)	

4. Spatiotemporal patterns in utilization of portability

We find that around 18% households in our sample used portability in a month on average. Further, approximately 27.5% households made at least one portability transaction in the 6-month time period (henceforth "portability users"). Among these, about 35% used portability in all 6 months whereas just under 19% used it only in one month. See Table 2 for more details. (Table A3 in the appendix gives the usage of portability for each month in our time frame of analysis.)

Table 2: Distribution of months of portability usage

	% portability users
One month	18.89%
Two months	11.35%
Three months	9.92%
Four months	11.70%
Five months	14.01%
Six months	34.23%

We classify portability users into three categories based on the temporal pattern of their usage. First, *sticky users* used portability for every transaction at a unique shop different from their home shop (hereafter "foreign shop") each time. In other words, all their transactions were portability transactions conducted at a unique foreign shop. Second, *conditionally sticky users* used home shop in some months and used a unique foreign home shop in other months. Third, *opportunistic users* used more than one foreign shop for their portability transactions during the analysis time frame. Table 3 shows that *sticky users* and *conditionally sticky users* make up almost 80% of portability users in the sample indicating strong preference among portability users for a unique foreign shop[xviii].

Table 3: Distribution of portability usage category

	% portability users
Sticky Users	39.31%
Conditionally Sticky Users	39.33%
Opportunistic Users	21.36%

Figure 1: Distribution of transactions by day-of-month

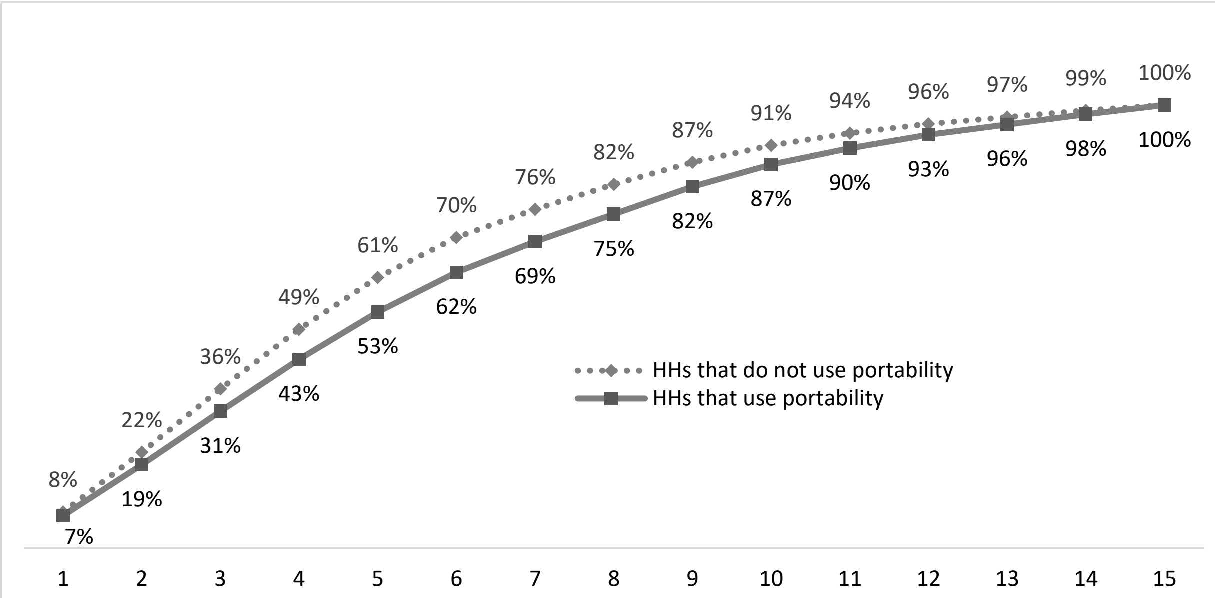
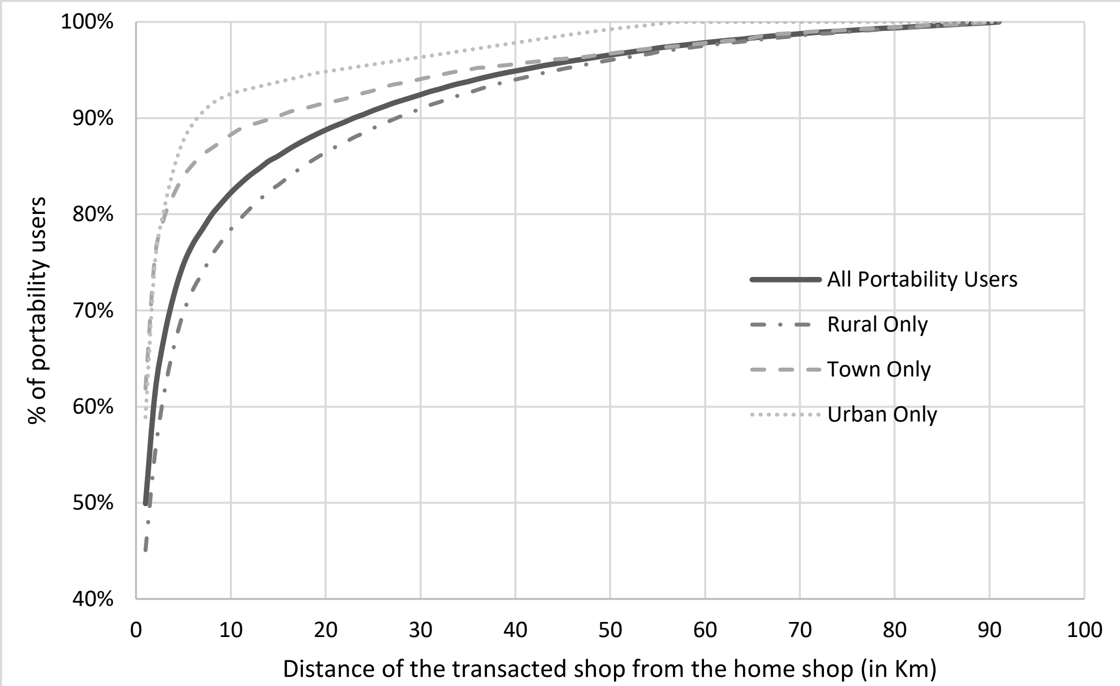


Figure 1 shows the percentage of households transacting by a given day of the month for households using portability and those not using it, respectively. We see that most households in either category collect their entitlements by the 5th of the month. However, for any given day of the month, a larger percentage of households not using portability have finished their transaction when compared to households using portability, i.e., households using portability transact later compared to those using their home shop.

Figure 2 depicts the distribution of distance between the home shop and the transacted shop for all portability users. We find that the median distance between the home shop and the shop used for transaction by portability users is 1.01 km. The median distance travelled by portability users in urban, town and rural locations is 0.74 km, 0.72 km and 1.42 km, respectively. 75% of portability transactions occur at a shop within 7 Km from the home shop of the household and about 3.4% of portability transactions occur at a shop greater than 90km from the home shop. The latter transactions are indicative of portability usage driven by migration, which was one of the policy goals of introducing portability (The Hindu, 2018).

Figure 2: Distribution of transactions by distance from home shop



These patterns suggest that the use of portability is different across households, driven by a combination of differential need for and ability to use portability. In the next section, we provide model-based evidence of association of portability usage with various factors identified in Section 3.

5. Drivers of portability utilization

5.1 Model Specification

We formulate a logistic regression model to examine the association between households' use of portability and various household and PDS characteristics.

$$ln\left(\frac{p_{it}}{1-p_{it}}\right) = \alpha_d + \boldsymbol{\beta}(\boldsymbol{PDSC})_{it} + \boldsymbol{\gamma}(\boldsymbol{HHC})_i + \varepsilon_{it}$$

where p_{it} = *Prob* (*Portability Usage* $_{it}$ = 1) and *Portability Usage* $_{it}$ takes the value 1 if household *i* has used portability in month *t* and 0 otherwise and $\boldsymbol{\beta}$ and $\boldsymbol{\gamma}$ are vector of coefficients that capture the association of portability usage to PDS characteristics (**PDSC**), and household characteristics (**HHC**), respectively. Finally, α_d represents district fixed effects, i.e., factors beyond PDS administration that are common to all households in a district such as those related to private markets and government administration. We use clustered robust standard errors with two-way clustering at the sub-district and month level[xix].

We estimate the above model by excluding around 64,899 observations (2.7% of the sample with all observations) that belong to households whose home shop did not register any transactions in that calendar month, i.e., $FPS\_open\_days_{it} = 0$. Based on our contextual understanding, we posit that these observations correspond to shop closures due to administrative reasons such as shop dealership changes, audits, etc. and usage of portability in these observations is unlikely to be driven by factors discussed in Section 3.

5.2 Main Results

Results for the main model are shown in Column (1) of Table 4 [xx] We find that for every additional day a home shop is open, there is 6.7% lower chance that households assigned to it will use portability. In contrast to our expectation, households assigned to shops managed by private dealers are less likely to use portability irrespective of the gender of the shop dealer. We find that households assigned to shops with a male dealer are 17.5% less likely to use portability whereas those assigned to shops with a female dealer are 16.8% less likely to use portability compared to households assigned to shops owned by cooperatives or self-help groups. As expected, households assigned to shops managed by women are less likely to utilize portability compared to those assigned to shops managed by men. However, the magnitude of this difference, although statistically significant, is small (0.7%).[xxi]

Not surprisingly, we find that the usage of portability increases as the number of alternate shops available for transaction in the vicinity of the household increases. In particular, every additional shop available within 0.5 km radius from the household's home shop is associated with an increase in likelihood of portability usage by 6.8%. As expected, this effect is lower if we consider a larger radius for alternate shops; 1.9% for every additional shop within 0.5 km to 1 km and 0.9% for every additional shop within 1km to 2km.

In line with our expectation, we find that more disadvantaged/vulnerable households are less likely to utilize portability. In particular, AAY households are 29.2% less likely to use portability compared to PHH households. Further, households residing in socially backward regions are 16.3% less likely to use portability compared to households in other regions. Similarly, households consisting entirely of elderly beneficiaries are 24.2% less likely to use portability. Finally, households in urban areas and towns are more likely to use portability compared to those in rural areas by 37.2% and 24%, respectively.

Table 4: Estimated marginal effects of PDS and household characteristics on portability usage

	(1) HHs with FPSs active	(2) All HHs	(3) HHs Transacting within sub-district	(4) HHs Transacting within 40 km
PDS Characteristics				
FPS open days	-0.067***	-0.129***	-0.081***	-0.071***
	(0.0044)	(0.0120)	(0.0051)	(0.0050)
Dealership (Base = Co-operative)				
Private male	-0.175***	-0.137***	-0.215***	-0.200***
	(0.0536)	(0.0550)	(0.0665)	(0.0587)
Private female	-0.168***	-0.186***	-0.207***	-0.191***
	(0.0533)	(0.0545)	(0.0662)	(0.0583)
FPS density (0.5 km)	0.068***	0.064***	0.091***	0.080***
	(0.0059)	(0.0056)	(0.0073)	(0.0065)
FPS density (0.5 km – 1 km)	0.019***	0.014***	0.020***	0.197***
	(0.0041)	(0.0040)	(0.0047)	(0.0044)
FPS density (1 km – 2km)	0.009***	0.008***	0.009***	0.009***
	(0.0019)	(0.0019)	(0.0022)	(0.0019)
Household Characteristics				
AAY	-0.293***	-0.263***	-0.277***	-0.282***
	(0.0204)	(0.0194)	(0.0236)	(0.0215)
SC/ST	-0.162***	-0.137***	-0.179***	-0.155***
	(0.0520)	(0.0537)	(0.0668)	(0.0573)
Elderly	-0.243***	-0.245***	-0.120***	-0.190***
	(0.0190)	(0.0178)	(0.0210)	(0.0198)
Location (Base = Rural)				
Town	0.371***	0.3796***	0.610***	0.364***
	(0.0533)	(0.0547)	(0.0647)	(0.0570)
Urban	0.238***	0.3403***	0.445***	0.278***
	(0.0754)	(0.0794)	(0.0878)	(0.0756)
Number of observations	2,328,981	2,393,880	2,233,940	2,274,725
Pseudo R^2	0.049	0.082	0.075	0.060
Wald Chi^2 (23)	8,585.38	8,727.59	8,098.26	9,016.94
Prob > Chi^2	0.000	0.000	0.000	0.000

We employ variance decomposition analysis (Grömping, 2007; Azen & Traxel, 2009; Tonidandel & LeBreton, 2010) to establish the relative importance of different factors in explaining the variation in the usage of portability. Results are shown in Table 5. We find that availability of choice as measured by number of shops around the household explains 67% of the variation whereas the location of the household (urban / town / village) explains 17% of the variation in probability usage. The third most dominant factor is the number of days the home shop is open, which explains 8% of the variation in portability usage.

Table 5: Variance decomposition of portability usage

	Variation explained
PDS Characteristics	
FPS open days	7.72%
Dealership	0.97%
FPS density (0.5 km)	37.02%
FPS density (0.5 km – 1 km)	19.23%
FPS density (1 km – 2km)	11.26%
Household Characteristics	
AAY	3.68%
SC/ST	0.74%
Elderly	1.90%
Location	17.37%

5.3 Robustness Checks

In this section, we estimate our models on two subsamples of our dataset in an attempt to rule out alternate explanations for portability usage that are not explicitly accounted for by the set of predictor variables included in our model. These include systematic closure of shops and migration related usage of portability.[xxii]

5.3.1 Systematic Closure of shops

While estimating our main model described in Section 5.1, we had excluded 2.7% observations where *FPS_open_days*$_{it}$ = 0 quoting administrative closures as a plausible reason. However, prolonged shop closures could also result from the dealer's deliberate decision or failures of technology that is required for the implementation of portability. In those cases, *FPS_open_days*$_{it}$ = 0 is also an indication of quality of service at the home shop and is a potential reason for usage of portability by households assigned to such shops. Hence, we re-estimate our model by including these observations. By definition, *portability_usage*$_{it}$ would take the value 1 for these observations, if a household transacts in that month. Column (2) of Table 4 presents the results of estimating our model including the observations for which FPS_open_days$_{it}$ = 0. We find that the coefficient of '*FPS_open_days*$_{it}$' almost doubles, from 6.7% to 12.85% but none of the other coefficients show significant change.

5.3.2 Migration related usage of portability

As discussed in Section 4, patterns of portability usage show that some households transact at foreign shops that are very far from their home shops, which maybe possibly driven by migration. As a result, the impact of our main predictor variables (PDSC and HHC) may be lower for such households and greater for households whose portability usage is at foreign shops that are closer to their home shop due to poor quality of service and inconvenience at their home shops. To examine this, we construct two proxy measures for potential migratory behavior of households based on their portability usage patterns and re-estimate our model by excluding these households and their transactions from the sample.

First, we identify 159,940 transactions (6.68% of the sample with all observations) in which a household's foreign shop (where the transaction occurred) and its home shop are in different sub-districts. The median distance between the home shop and foreign shop for these observations is 22.81 km. Column (3) of Table 4 contains the results of estimating equation (1) on a subsample excluding these observations. As expected, the association of home shop and administrative characteristics with portability usage is higher in this subsample. Specifically, coefficient of '*FPS_density (0.5 km)'* increases from 6.7% to 8.1% whereas the coefficient of '*FPS_open_days*' increases to 8.1% from 6.8%. In addition, we find that the incremental usage of portability in urban location or town (compared to rural location) is much larger for this subsample of transactions within the same sub-district. This suggests that a larger proportion of portability usage from rural households is likely to be due to migration compared to those in urban locations and towns. Equivalently, service quality seems to be a more prominent reason for portability usage in urban locations and towns.

Second, we identify 119,155 transactions (4.97% of the sample with all observations) in which the distance between a household's home shop and the foreign shop (where transaction occurred) is greater than the 95th percentile (approximately 40 km). Column (4) of Table 4 contains the results of this estimation. Here too, we find that the effect of home shop characteristics and administrative characteristics is higher compared to that in the full sample shown in Column (1) of Table 4.

6. Discussion

Poor quality of service delivery in food security programs is a major impediment to alleviating hunger in developing countries. Policy makers in various countries have attempted to address this issue by reducing monopolistic power of private agents and increasing the choices for beneficiaries. In this paper, we analyze a large-scale intervention in India's Public Distribution System termed *'portability'*, wherein beneficiaries were provided the choice of availing their entitlements from any of the licensed shops in the state. Using PDS program data in the state of Andhra Pradesh, we find that, on average, 18% of households exercised this choice every month. Given that our study period (March 2018 to August 2018) is almost three years after the introduction of portability, we believe that this is an accurate reflection of the long run utilization.

To begin with, households whose home shops were closed more often were found to utilize portability to a greater extent. In the absence of portability, these households would have had to resort to open market purchases or would have had to make multiple visits to their home shop to obtain their entitlements. This highlights the possible impact of portability on the economic welfare of the beneficiaries. However, these benefits are observed to be heterogeneous across household types. In particular, it is important to note that the usage of portability was significantly lower among vulnerable populations, the rural, the poor, the elderly and the socially disadvantaged. This highlights the limitation of technology-driven enhancements in welfare programs as the sections of the population who are likely to benefit the most from them are also least likely to be aware of those and, as a result, least likely to appropriate their benefits. Another plausible reason for this heterogeneity may be prevailing social power structures that cannot be overcome merely through technology implementation. For instance, in our field visits, we observed that SC/ST households were often not allowed to use a shop located in a street/neighborhood, where large portion of residents belong to the upper castes.

Our results highlight the importance of easy access to alternate shops as measured by the density of shops in the extreme geographic proximity of households (less than 0.5 km). In other words, these results suggest that provision of portability does not automatically dismantle the monopoly of shop dealers. In our data, close to 27% of households did not have an alternate shop within a radius of 1 km from their home shop. It is reasonable to argue that cost of accessing portability is high for these beneficiaries and the monopoly of shop dealers continues to persist in these regions. Even in regions that have alternate shops, shop dealers may collude amongst each other to not honor requests from beneficiaries who are not assigned to their shop. Reports of such cartels have already emerged from the state of Chhattisgarh (Sharma & Gupta, 2017). Given that cartels with a smaller number of players are stronger and more likely to sustain for a longer period (Hamaguchi, Kawagoe, & Shibata, 2009), the issue of shop dealers colluding might be more acute in regions with low shop density.

Though our results provide valuable insights into the utilization of portability by beneficiaries and the underlying drivers, we acknowledge that our study design has certain limitations. First, our outcome variable, usage of portability, may not have a simple, direct relationship with beneficiary welfare due to the complex dynamics involved in the response of shop dealers. For instance, on the one hand, if all FPSs improved the quality of their service due to the competition induced by portability, households may not need to use portability and yet experience welfare improvement. However, on the other hand, as mentioned above, if shop dealers colluded to not serve each other's beneficiaries, the utilization of portability may be still low. Second, any evaluation of welfare implications of providing portability has to also account for the potentially higher costs incurred by both beneficiaries and the program. Beneficiaries are likely to incur higher transportation and time costs to avail their entitlements from an alternate shop. Similarly, introduction of portability can increase variability in demand at each shop and additional inventory may be required to reduce the chance of stock outs. Indeed, we find that on average the total monthly inventory of grains carried by shops in AP is 22% more than the total quantity needed by the state. Consequently, operational policies may need to be modified to balance the trade-off between higher beneficiary welfare and program costs.

Further research on above issues based on these early experiences is needed to inform the expansion of this innovation at the national level as currently envisioned by the Government of India (India Today, 2019). Findings from future studies can also inform the efforts of several other developing countries such as Indonesia, Bangladesh, Ethiopia and Malawi that are currently in the midst of revamping their food security programs by providing them with options beyond the dichotomy ingrained in the cash vs. in-kind and privatization vs. government monopoly debates (Ahmed, Quisumbing, Nasreen, Hoddinott, & Elizabeth, 2009; Bailey & Hedlund, 2012; Fernández, 2015; Banerjee et al., 2017).

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Appendix

Table A1: Average proportion of shops open across 6 months

First 2 days	82.5%
2nd – 4th day	88.3%
4th – 6th day	87.7%
6th – 8th day	79.3%
8th – 10th day	78.7%
After 10th day	67.2%

Table A2: Correlation Matrix

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1) Shop open days	1.00								
(2) Dealership	0.02	1.00							
(3) FPS_density (0 – 0.5 km)	-0.04	0.03	1.00						
(4) FPS_density (0.5 – 1 km)	-0.04	0.04	0.58	1.00					
(5) FPS_density (1 – 2 km)	-0.03	0.05	0.46	0.79	1.00				
(6) AAY	0.00	0.00	-0.02	-0.02	-0.02	1.00			
(7) SC/ST	0.07	-0.02	-0.09	-0.08	-0.08	0.02	1.00		
(8) Elderly	0.01	-0.00	-0.02	-0.03	-0.02	0.08	0.01	1.00	
(9) Location	-0.07	0.04	0.33	0.58	0.64	-0.02	-0.09	-0.02	1.00

Table A3: Portability utilization by month

Month	% households utilizing portability
March 2018	16.8%
April 2018	17.1%
May 2018	18.1%
June 2018	18.3%
July 2018	18.7%
August 2018	18.3%

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[i] Currently, ten states (Andhra Pradesh, Chhattisgarh, Telangana, Gujarat, Haryana, Rajasthan, Karnataka, Jharkhand, Tripura and Delhi) in the country have introduced portability and there is consideration of introducing portability throughout the country (India Today, 2019).

[ii] Food entitlements for a month are pre-determined by the government and typically include, but are not limited to, commodities such as rice, wheat, pulses and sugar.

[iii] This data is obtained from Agmark portal - https://agmarknet.gov.in/

[iv] Based on the new article - https://www.thehindu.com/news/cities/Hyderabad/ration-dealers-will-be-paid-increased-commission-eatala/article23315122.ece

[v] In most states, the priority households are entitled up to 5 kg of rice per person per month at the issue prices of ₹1. The AAY households can claim up to 35 kg of food grains per household per month at the same price.

[vi] The latitude and longitude data could not be identified for 7K shops. For these shops, we use the FPS address to identify the most granular geographic location (village/colony/street number) and populate the corresponding coordinates extracted using Google API. Further, we test the accuracy of the extracted co-ordinates by triangulating them with village level coordinates populated in national village census data 2011.

[vii] The exhaustive list of key words searched to identity FPS not manged by private dealers is obtained by a combination of substring analysis in SAS and manual inspection. The list includes various combinations of the key words mentioned below – SHG, Co-op, MSS, Society, PACS, VRA, GPMC, Mahila, Sangham, Group, DWARCA, Podupu, Cooperative.

[viii] We test the algorithm's accuracy by administering it on a sample data drawn from the household dataset, for which the gender is already known. Gender predicted by the algorithm matches with the actual gender in 96% of the cases.

[ix] Our search is based on a fuzzy match using Levenstein distance. If the village/city name extracted from the FPS address is more than 80% similar to the ones populated in census, we consider it a match. In cases where the FPS city/village name finds more than one match in census data, we choose the census village/city name with the highest percentage match.

[x] Census is an enumeration exercise carried out by the Ministry of Home Affairs, Government of India. This exercise is carried out once in every 10 years. This exercise was last conducted in the year 2011 and the data generated from it is shared in the link below – http://censusindia.gov.in/2011-Common/CensusData2011.html

[xi] To ensure the robustness of our results, we repeat our analysis on 4 such independently drawn random samples and all our results continue to hold.

[xiii] There is a likelihood that a shop is kept open but there are no transactions registered. However, based on our semi-structured interviews, such likelihood is very less. We gathered that most FPS dealers have secondary occupations such as farming and small-scale businesses. They typically open the FPS at the start of the month, keep it open for a consecutive streak of days and move on to other occupations during the rest of the month. Therefore, it is reasonable to believe that our definition, although not perfect, is a close proxy to the actual number of days a shop is kept open.

[xiv] Our data does not capture the details of the individual within a household who transacts at the FPS.

[xv] We consider different values of x (0.5 Km, 1 Km, and 2 Km), which we calculate as the Haversine distance based on the latitude and longitude of the shops from the *FPS dataset.*

[xvi] The governments of most states share this information on their webpages. The source data used in this analysis is also scraped from one such webpage. In addition, in some states such as Chhattisgarh, we also observe such information being shared with beneficiaries through SMSs on mobile phone.

[xvii] Identification of sub-district as vulnerable is based on the percentage of its households belonging to primitive tribal groups, SC and ST categories. We compute these percentages across all 664 sub-districts in the state. We categorise a sub-district as vulnerable if the percentage of households belonging to any of these categories is higher than the 75th percentile. The 75th percentile for primitive tribal groups, SC and ST are 2%, 30% and 31% respectively.

[xviii] We did not find any systematic statistical difference between these groups based on observable household characteristics

[xix] Error terms are likely to be correlated within time period (months) across FPSs. The correlation could arise because of unobserved household behavior and characteristics that are persistent over time. Further, Households in the same sub district are likely to be similarly impacted by factors such as change in administration, focus on PDS related developmental initiatives.

[xx] We check the robustness of our model by estimating it for the entire sample. Those estimation results are shown in Column (2) of Table 4 and are discussed in Section 6.

[xxi] 0.8% is obtained by measuring the difference between the coefficients against FPSs managed by men (-0.175) and FPSs managed by women (-0.168).

[xxii] Previous studies have found that effectiveness of public welfare programs diminished in communities that are farther from administrative headquarters (Kraay et al 1999; Krishna and Schober 2014). We test this hypothesis on a subsample of rural households but do not find evidence to support it in our context. We omit the discussion of these results for brevity.