Household (Under) Adoption of Sanitation: Externalities and Borrowing Constraints*

Sanghmitra Gautam†
University College London

Job Market Paper
For the latest version click here

14th January 2017

Abstract

This paper analyses under-adoption of sanitation and the effectiveness of loans and price subsidy policies to increase coverage in the developing world. Under-adoption may be the result of externalities and borrowing constraints: while sanitation is an expensive investment for many poor potentially liquidity constrained households, it also generates positive health externalities. To investigate the impact of the two policies on sanitation coverage I estimate a dynamic model of household demand on a unique dataset from rural India. The model embeds both sources of market failure in order to compute equilibrium adoption levels under the loan and the subsidy policy. Using simulations from the estimated model, I study optimal policy design in an equilibrium setting with potential multiple equilibria. Counterfactual analysis reveals that existing sanitation levels are on average 53% below the social optimum, implying under-adoption. I find price subsidies to be more cost effective at increasing sanitation coverage. However, the policy impacts are heterogeneous by coverage levels: in villages with low coverage loans are equally, if not marginally more, effective. A price subsidy has a high social rate of return where externalities account for a substantial fraction of the policy impact. While a sanitation loan policy generates smaller social returns it is also cost efficient under targeted delivery.

Keywords: Externalities, Subsidies, Liquidity constraints, Welfare, Dynamic games

*I am grateful to Orazio Attanasio, Aureo De Paula & Michela Tincani for their feedback and support. I also thank Alberto Bisin, Valerio Dotti, Eric French, Toru Kitagawa, Jeremy McCauley, Rory McGee, Davide Melcangi, Paul Andrés Rodríguez, Mark Rosenzweig and seminar participants at UCL. I thank EDePo, Institute for Fiscal Studies (IFS) & Britta Augsburg for access to the Household level dataset and the Municipal Corporation of Gwalior, India for their advice & assistance in collecting the cost/price data. All remaining errors are my own.

†Department of Economics, University College London (UCL), 30 Gordon Street, WC1H 0AX United Kingdom. Email: sanghmitra.gautam.09@ucl.ac.uk web: *https://sanghmitragautam.github.io*

1 Introduction

Close to 2.5 billion people on the planet (≈ 35% of the population) do not have access to basic sanitation (WHO-UNICEF 2014).[1] Lack of sanitation has detrimental effects on individual health, economic and social well-being (Mara, Lane, Scott & Trouba 2010).[2] In recent years there has been significant policy interest in the developing world to increase sanitation adoption amongst households.[3] Finding strategies to tackle under-adoption has become a policy imperative. Governments have used many different policies to incentivize adoption. However, there is substantial disagreement as to which policies are effective at increasing coverage and at an affordable cost to developing countries. The disagreement arises from contrasting views on which market failure generates under-adoption of sanitation.

Two often cited market failures are borrowing constraints and externalities. First, in developing countries with limited or non-existent credit markets, a liquidity constrained household may find it difficult or impossible to purchase sanitation. Second, sanitation generates positive externalities (Duflo, Greenstone, Guiteras & Clasen 2015). For example, in a similar manner to vaccination; an increase of sanitation adoption amongst neighbouring households reduces the risk of infection and likelihood of being sick for an individual (Geruso & Spears 2015, Hammer & Spears 2013, Spears 2012, 2013, Augsburg & Rodriguez 2015). Such spillover effects are not necessarily internalised by an individual resulting in inefficient adoption.

This paper analyses if there is under-adoption and its extent using data from India, where only 37% of the population has access to sanitation. Having established under-adoption, I ask: If the objective of the policy makers is to maximize coverage subject to government budget constraints, are sanitation loans or price subsidies more effective at increasing adoption? Moreover, I also study the welfare implications of the two policies.

To answer these questions, I develop and estimate a dynamic equilibrium model of sanitation choices of households. The model has two key features. First, it allows for households to be borrowing constrained in their consumption and sanitation adoption choice. Second, to capture the externalities households make interdependent adoption choices. I model the household decisions to adopt sanitation and to save over the life-cycle within a strategic setting of an incomplete information game. Interdependent adoption captures numerous possible channels that can generate externalities.[4]

[1]Basic sanitation refers access to a toilet/bathroom facility

[2]The World Bank estimates that increase in sanitation coverage can reduce diarrhoeal disease related child mortality by more than a third.

[3]Over the period 2008 − 2015 the Gates Foundation has allocated approx USD. $650 million under the water, sanitation and hygiene (WaSH) program towards increasing sanitation coverage Bill & Melinda Gates Foundation (2011).

[4]The framework allows for externalities to arise from different channels. For example, there is a biological contagion channel which affects health but there may also be information spillovers with neighbours sharing knowledge on the benefits from adoption. In addition social norms and peer pressure may also play a role.

The challenge of solving and estimating the model arises because agents do not optimise in isolation but instead solve an inter-related system of dynamic programming problems. As is typical of many strategic decision models, multiple equilibria may arise depending on the strength of the externality. This poses challenges in estimation and counterfactual analysis, especially when one is unwilling to specify an arbitrary selection rule.

First, this paper builds on the estimation methodology in Hotz, Miller, Sanders & Smith (1994) and Bajari, Benkard & Levin (2007) by combining a two stage and full solution estimation methods. I demonstrate that by making a small trade-off under the two-step approach; by numerically solving a part of the model, it is possible to have an estimation method that can accommodate a richer set of strategic demand models for a small increase in computational cost.

Second, this paper proposes a method to conduct counterfactual policy analysis that circumvents the typical issues of multiplicity. Specifically, the burden of solving for all possible equilibria and an additional challenge with simulation ensues when the existing selection rule is not policy invariant and is no longer valid under different counterfactuals. This affects the validity of the policy implications derived which are a function of the underlying selection mechanism. A common approach, undertaken in applied work, is to specify an equilibrium selection rule under estimation with the implicit assumption that the selection rule does not change in counterfactual scenarios.[5] This paper takes an alternative route where I instead bound the set of counterfactual policy outcomes that could be sustained under different selection rules. I do this by first characterizing the conditions under which the model implies strategic complementarity in the sanitation adoption decisions. This allows me to establish an order over the set of equilibria thereby bounding the set using the highest and lowest equilibrium. The equilibrium bounds are used to characterize the region of the policy impact that could be sustained in equilibrium under counterfactual scenarios.

There is an active literature on estimating both static and dynamic games that explicitly address the issue of multiple equilibria. This paper is related to the extensive literature on the estimation of dynamic models using the Hotz & Miller (1993) two-step Conditional Choice Probability (CCP) approach. The literature comprises of numerous extensions to the original two-step estimator for both single-agent and strategic interaction models. More recently, Aguirregabiria & Mira (2007), Bajari, Benkard & Levin (2007), Pakes, Ostrovsky & Berry (2007) and Pesendorfer & Schmidt-Dengler (2008) have developed estimation procedures that allow one to recover the primitives that underlie dynamic choice games. In contrast to the estimation literature, there is a smaller body of work on the problem of conducting counterfactual policy simulations under multiple equilibria. The idea to bound the set of equilibria has previously been exploited in the literature both for the purpose of estimation and simulation. This includes work by Jia (2008), De Paula (2009), Lee & Pakes (2009), Björkegren (2014) and Reguant (2015).[6] In terms of counterfactual simulation, Björkegren's (2014) study of mobile handset adoption in Rwanda is closest to this paper. However,

[5]For example in a recent working paper by Fu & Gregory (2016) study household rebuilding behaviour post Katrina hurricane where the neighbour's rebuilding decisions induces amenity spillovers. The paper assumes a specific equilibrium selection rule under which the model is both estimated and simulated for counterfactual policies.

[6]Jia (2008) establishes bounds for the possible set of fixed points under specific selection rules in order to ease the burden of estimating the model.

differently from Bjorkegren the simulation method in this paper does not employ the assumption of perfect foresight.

The model is estimated using a two period household panel data from India. In addition to sanitation adoption, I observe a rich set of household characteristics including asset accumulation, earnings, household demographics and cost of sanitation. The survey covers time periods 2009/10 and 2012/13 and includes information on key demographic features at the village level. Additional information on the cost of sanitation measure was collected at across villages in 2012.

By comparing the existing sanitation levels in the data with the socially optimal level of adoption from the estimated model, I quantify the extent of under-adoption. First, I compare the cost effectiveness of providing sanitation price subsidies differently from loan policies to increase coverage and compute welfare gains under each policy. Second, I decompose the policy effect into its direct and indirect components i.e., externality on an individual household's demand response. Lastly, I use the structural framework to derive implications about optimal policy design and cost efficiency.

An advantage of a structural approach is to be able to simulate the impact of counterfactual policies on adoption decision from changing the direct costs of sanitation, for example through the provision of price subsidies or loans that incentivize adoption. Compared with a utilitarian social planner solution, existing coverage levels are on average 53% below the socially optimal level, implying under-adoption. This wedge is induced by the under valuation by each household of the total benefits derived from adoption. Under cost effectiveness considerations, I find price subsidies to be, in general, more effective at increasing sanitation coverage. However, the policy effects are heterogeneous where loans are found to be equally, if not marginally more, effective in villages with no sanitation coverage. In contrast, I find that price subsidies compared with sanitation loans are more effective at increasing sanitation coverage within villages with mid to low initial sanitation levels. This is because a subsidy policy generates a larger feedback effect in the presence of externalities which propagates through the entire village resulting in a larger shift in the equilibrium sanitation level. Instead sanitation loans are found to be more cost effective in villages with close to zero initial sanitation prevalence.

I find that the additional adoption induced by a price subsidy policy generated positive externalities equivalent to $Rs. 3,181$ (lower bound) and $Rs. 6,253$ (upper bound) of welfare gain for households whose adoption choice was not directly affected by the program. While the policy generated a larger gain equivalent to $Rs. 10,008$ (lower) and $Rs. 12,511$ (upper) for the recipient household directly affected by the policy. The impact of the subsidy policy shifted bounds on net welfare upwards by $Rs. 1,380$ (lower) and $Rs. 3,883$ (upper). A significant proportion of this gain 33% (lower) to 72% (upper) in surplus is accrued indirectly through the spillover effects.

These findings highlight the fact that, with the presence of externalities, accounting for and quantifying the effect of equilibrium interactions among households is essential to understand the impact of policies. This paper argues that subsidies affect household welfare both directly by reducing the relative price for sanitation but also indirectly through an externality that affects the relative cost faced by an individual household. This analysis is consistent with evidence from field experiments on sanitation demand and contributes to the literature on the topic of sanitation. In particular, it complements a recent study by Guiteras, Levinsohn & Mobarak (2015) which analyses the impact of different policy interventions on sanitation take-up behaviour among households in Bangladesh using a randomized experiment. The experiment contrasts between policies that provide information on the benefits of having sanitation at home and policies that directly subsidize the cost of adoption through price subsidies along with a control group. Their analysis finds evidence of positive spillover effects from adoption on households other than the recipient beneficiary both in adoption decisions and health outcomes.

The remainder of the paper is organized as follows. Section 2 provides a background and description of the data. Section 3 presents the model of household sanitation choice and the identification assumptions. Section 4 describes the estimation strategy and discusses the parameter estimates and model fit. Section 5 describes how the estimated model is used to simulate the equilibrium sanitation adoption behaviour under counterfactual policy interventions. Results from counterfactual policy analysis are presented in Section 6. Section 7 concludes.

2 Context and Data

2.1 Sanitation in India

Despite substantial evidence on the importance of sanitation for health and human capital development, progress towards increasing access to sanitation in India has been extremely slow. For example, in rural areas, the fraction of households without a toilet decreased by only 8.8 percentage points between 2001 and 2011, from 78.1% to 69.3% (Ministry of Rural Development 2012). While a number of innovative and successful approaches have increased access to sanitation on a small scale, the national average of 37% sanitation coverage is well below the global average of 64%.[7] The topic of sanitation provision has also garnered important political interest within the country. The current Prime Minister Narendra Modi launched the "Swachh Bharat Abhiyan" (Clean India Mission) initiative which proposed to provide toilets/sanitation to all 110 million rural households that currently do not have one, at a cost of *USD* 22.0 billion (Ministry of Rural Development India, 2014).

Poor sanitation has been linked with causes of intestinal diseases which reduce the absorption of calories and nutrients, and leads to malnutrition and impaired cognitive development among children. There is also a growing body of work within the economic literature, that quantifies the impact of sanitation prevalence on individual health outcomes especially for children. For example, a recent working paper by Geruso & Spears (2015) investigates the impact of poor

[7] The national average of 37% is across rural and urban populations. Sanitation coverage in rural India is estimated at 21.1% while the number for urban population is close to 54% (data.worldbank.org)

sanitation coverage on infant mortality in India. By instrumenting for local sanitation prevalence with the religious composition of neighbourhoods to account for endogeneity of sanitation coverage, they find evidence of large infant mortality externalities associated with the lack of sanitation amongst neighbours. Specifically, their analysis finds a decline in $2.6 - 2.9$ infant deaths per 1000 with a 10% increase in sanitation adoption levels. Augsburg & Rodriguez (2015) use the data on sanitation price variation as an instrument for the sanitation prevalence across village.[8] Their instrumental approach suggest a significant increase in child height for age $z - scores$ by 0.15 standard deviations with a 10% increase in sanitation prevalence.

In contrast, there are few examples that study demand for sanitation and the factors/market failures that affect household choice. An exception to this is a recent paper by Guiteras, Levinsohn & Mobarak (2015) based on a randomized policy experiment conducted in Bangladesh. The experiment measures the impact of different policies: price subsidies, supply-side and information provision, on household sanitation adoption. The findings suggest that lack of information, about the benefits of improved sanitation, or lack of access to markets for sanitation components are not the key deterrents to a household's investment in sanitation. Instead, the significant increase in sanitation ownership and usage among subsidy (price subsidy) recipients suggests that financial constraints might be an important limiting factor in their context. The increased probability of sanitation ownership among non-recipients also suggests that purchasing decisions of one's neighbours affect a household's own purchasing decisions - even without a subsidy incentive. Furthermore, the increase in sanitation adoption rates as the proportion of subsidy voucher recipients suggests the presence of spillover effects and inter-linked adoption decision. My analysis reveals the extent of under-adoption accrued due to externalities as well as induced by binding financial constraints.

2.2 Data Overview

The data for the empirical analysis comes from a household panel survey conducted under the FINISH program (Financial Inclusion Improves Sanitation & Health) in India during the periods $2009 - 10$ and $2012 - 2013$. The program aims to improve the living standards of poor communities by implementing projects that improve sanitation, hygiene and waste management across the country. The overall objective is to increase sanitation access and coverage and thereby improve the living and economic conditions for poor households that otherwise lack access to basic sanitation. Under its sanitation and hygiene program, FINISH provides sanitation facilities at the household level through a combination of micro-credit lent by Microfinance Institutions (MFIs) or local banks, and/or price subsidies (subsidize the cost of adoption). In addition to the provision of financial incentives, the interventions also include a self-contribution component and health insurance incentives. It is important to mention that though the data was collected under the FINISH program, it does not include the impact of any policy intervention implemented.

[8] The analysis in Augsburg & Rodriguez (2015) also makes use of the dataset employed in the empirical analysis in this paper. They additionally use variation in the cost (price) of sanitation, collected independently in Gautam (2015) and this paper as an instrument. Their analysis provides constructive evidence on the presence of significant positive externalities on child health in the data used.

Descriptive Statistics.

The data used in this project comes from the regional locality of Gwalior located in the state of Madhya Pradesh, India. With only 28% of population with access to sanitation, Madhya Pradesh ranks 30 out of a total of 36 states in the country in order of sanitation coverage. The sample size comprises of 1451 households observed over the two survey periods $2009-10$ and $2012-2013$ from 42 village groups. The FINISH sample comprises of a detailed household survey which includes a rich set of information on household demographics, household members and household head, education, earnings, asset accumulation and consumption values as well as information on sanitation adoption. The dataset also comprises of village level demographics which includes information on daily wage rate for labour, presence of drainage infrastructure and availability of public sanitation facilities within the village.

Table (1) provides descriptive statistics for a few variables of interest across the two period panel. The household head is on average 43 years of age with primary school education.[9] A typical family consists of 5 household members half of whom are female. Home ownership rates are high with close to 90% of household heads owning their house. Cash-in-hand refers to the total annual income and liquid assets available to the household for consumption. The stock of assets which also includes savings in the bank is between 8% and 10% of the total available resources for consumption. Income earnings and stock of asset values are deflated to 2010 values.

Table 1: Descriptive Statistics

	Data:S1		Data:S2	
Variable	**Mean**	**std. dev**	**Mean**	**std. dev**
Household				
Age of Household Head (yrs)	42.56	(13.22)	43.61	(13.81)
Education level of HH head (yrs)	4.61	(0.34)	4.87	(0.32)
Nr. Of Female HH members	2.54	(1.29)	2.89	(1.40)
Household size	5.20	(1.03)	5.67	(1.10)
Dwelling ownership	0.89	(0.314)	0.90	(0.309)
Cash-in-hand (Rs.)	57,112.32	(16,167)	68,331.69	(18,128)
Savings, Liquid Assets (Rs.)	4,482.13	(5,073)	7,674.34	(4,899)
Village/Group				
Drainage Infratructure	0.43	(0.495)	0.47	(0.461)
Community Sanitation presence	0.51	(0.501)	0.54	(0.489)
Cost of building Sanitation (Rs.)	8,628.00	(1150)	8,981.00	(1256)
Sanitation coverage	0.41	(0.304)	0.61	(0.287)
Nr. of groups	42			
Nr. of observations	1,451			

Notes: This table provides descriptive statistics for key household and group variables across the two sample periods. Monetary values in the second period are deflated to first period values. The GDP (per capita) Rs. 167,600 (2010 estimate). £1 $\approx Rs. 100\,(INR)$.

[9] Primary School in India is up to year 5 with a total of 12 years of primary and secondary education.

Cost of Sanitation.

Data on the cost of sanitation was collected in July/August 2012 across all villages.[10] The price measure is based on the cost of building the most common type of sanitation facility in the local region i.e., 'Twin Pit Pour Flush' (TPPF) unit. All households within a village face the same price. The price measure comprises of two components: the total cost of raw material and the cost of labour required to build the facility itself. The price measure varies across villages in both components. The formula applied to construct the price measure is as follows:

Price variation across villages g:

- $wage_g$: Daily (informal) wage rate which varies across villages.
- $days$: Approximate time to construct a 'Twin Pit Pour Flush' (TPPF) variation between $3-4$ days. TPPF is the standard and most popular sanitation design unit implemented by the government under the Total Sanitation Campaign (T.S.C)
- $cost_g\,(raw\,materials)$: Cost of raw material (cost of five principle materials used in the construction of a TPPF unit) which include — Bricks, Mortar, Tiles, Ceramic fixtures & Tin sheets.

$$price_g = wage_g \times days + cost_g\,(raw\,materials) \times quantity(kilogram/piece/unit) \qquad (2.1)$$

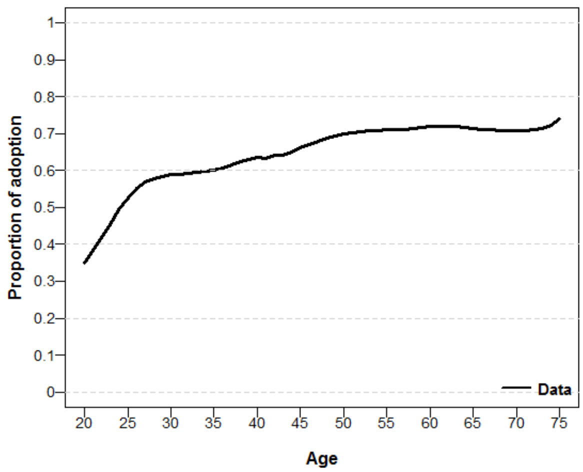
The main source of variation arises from the cost of raw materials which varies across villages and comprises close to 70% of the total cost of sanitation incurred. A point to note here is that the raw materials used in sanitation are widely produced and demanded in the region on a large scale for other domestic and commercial construction. The demand for these products for the purpose of building sanitation constitutes a very small proportion of the overall demand for the goods in the region.[11]

Age profiles. The life-cycle profiles of interest include sanitation adoption and asset accumulation by age of household head. Figure (1) depicts the dynamics that the model should be able to replicate. Appendix (A) describes the way in which life-cycle profiles are obtained using data from different age cohorts. Sanitation adoption varies over the life-cycle of a household head with 37% prevalence among 20 year household heads to just over 70% prevalence by the age of 75. There is a relatively steeper increase in the proportion of adoption between the age of 20 and 26 while adoption tapers off to be flat past the age of 55. The asset stock profile (per Rs. 1000) depicts a hump shaped profile with a steady accumulation of assets up to the age of 55, past which the household de-cumulates to almost it's initial stock of assets by the age of 75.

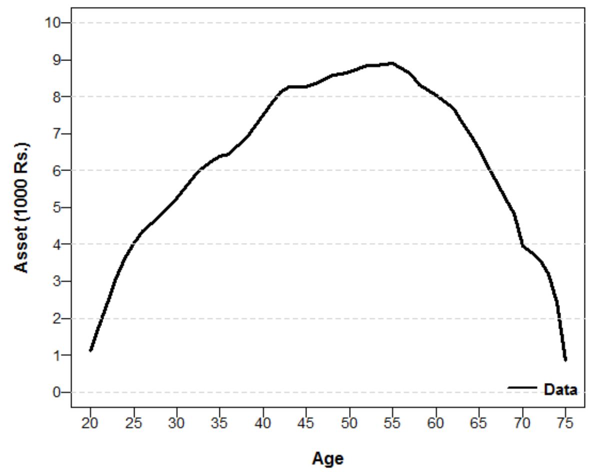
[10]The information used to construct a measure for the cost of sanitation was collected independently of the household survey. I received helpful advice and assistance from the Gwalior Nagar Nigam Seva municipal authorities in the collection process.

[11]Table (9) in the appendix provides details on variation of price and sanitation prevalence by village.

Figure 1: Life Cycle Profiles



(a) Proportion of Sanitation Adoption



(b) Assets over the Life Cycle (1000 *Rs.*)

3 Model

This section describes the model which provides a framework to evaluate the impact of different policy interventions on household demand for sanitation. A household is taken to be a single decision making unit where the household head is identified as the primary decision maker. The model closely matches the observed adoption behaviour over the life-cycle, and is designed to capture the key trade-offs faced by a decision making household. Specifically, the structure incorporates features that influence a household's net utility from adoption: (i) the cost of building sanitation, (ii) the impact of binding liquidity constraints, (iii) the strength of the idiosyncratic taste shocks for having sanitation at home and, (iv) the impact of changes in the sanitation coverage within the village. The increase in sanitation coverage within a village can generate spillover effects that are not necessarily internalized by individual households. The impact of such externalities is captured through an interdependence in household demand for sanitation, where the gains derived from having sanitation also depend on the adoption decision of the village as a whole.[12]

The interdependence is modelled as a strategic interaction among households under incomplete information.[13] An individual household evaluates it's private utility from adoption against the social benefits it derives through the spillover effects. The key difference of the structure from a single agent model is that instead of acting in isolation households solve an inter related system

[12]Externalities in the model can be generated from different underlying mechanisms for e.g. health externalities, information spillovers, amenity agglomeration effects as well as peer conformism effects.

[13]Under incomplete information the information set of a decision making household is only partially observed by other households including the econometrician.

of dynamic programming problems given expectations about adoption decision of other households. Under rational expectations, in equilibrium a household's actions must be optimal given their beliefs and their beliefs must be correct on average. In addition, households are also restricted from borrowing against their future income. Thus, the present decision to buy sanitation induces an inter temporal trade-off with savings that could instead be used to insure future consumption against income shocks.

This section describes the primitives of the model, including household's information set and choices, state variable transitions and the timing of choices along with a specification of the household problem. I also describe the Markov Perfect Equilibrium within the model and possible multiplicity of equilibria. Lastly, I discuss the identification of the primitives and the assumptions employed to identify the parameters of interest.

3.1 Model Specification

There are a finite number of village groups indexed by $g = 1, ..., G$ and each village is the relevant reference group for a household. Let N denote the set of households that belong to each village indexed by $i = \{1, 2, ..., N\}$.

Choice Set. A household head makes decisions based on his or her age a over a finite horizon, where $a = 20, ..., 75$ and $\mathcal{A}$ denotes terminal decision making age. In addition, within a village different 'aged' households interact with each other where the dynamics evolves over calendar time $t = 1, ..., \infty$.[14] At each age a until terminal age $\mathcal{A}$, a household who is alive at time t can choose a pair (d_{it}, c_{it}), where $d_{it} \in \mathcal{D}_{it} = \{0, 1\}$ denotes choice to adopt sanitation today or wait until the next period:

$$d_{it} = \begin{cases} 0 & Non\, adoption \\ 1 & HH\, adopts\, sanitation \end{cases}$$

and $c_{it} \in \mathcal{C}_{it}$ denotes the consumption choice today which determines the amount saved for tomorrow A_{it+1}. A household's choice to adopt sanitation is an absorbing state where $k_{it} = k_{it-1} + d_{it}$ denotes status of sanitation adoption.[15] In each period t, different 'aged' households simultaneously decide whether or not to adopt sanitation. The vector of all household actions in period t is given by $d_t = (d_{1t}, d_{2t}, ..., d_{Nt})$ and $c_t = (c_{1t}, c_{2t}, ..., c_{Nt})$.

[14] The village economy can be viewed as an overlapping generations framework of household heads aged between $20 - 75$ years old.

[15] I do not observe destruction of sanitation units over the two samples in the data. Also treating sanitation adoption as a binary choice is reasonable in the context of rural India where almost all household have at most one toilet/sanitation facility per household.

State variables. Each household i is characterized by a vector of state variables that affect utility: x_{it} and ε_{it}. A household's decisions are based on the age of the household head a_{it}, stock of assets A_{it}, income y_{it}, state of adoption k_{it-1}, cost of sanitation adoption *price* and the level of existing sanitation coverage $\overline{k}_{t-1}$ within the village it resides. Decisions are also based on a household specific idiosyncratic taste for sanitation $\varepsilon_{it} = \left[\varepsilon_{it}^{d=1}, \varepsilon_{it}^{d=0}\right]$ which is a private information shock possessed by household i and unobservable to all other households $-i$ and the econometrician. Household i specific state vector is denoted by $\left(x_{it}, \varepsilon_{it}^{d}\right) = \left(a_{it}, A_{it}, y_{it}, k_{it-1}, \overline{k}_{t-1}, price, \xi_{it}, \varepsilon_{it}^{d}\right)$, where $\xi_{it} \in x_{it}$ is an allowance for measurement error in income.[16] Both taste shocks ε_{it} and measurement error ξ_{it} are assumed to be independently distributed (*i.i.d*) across households and time periods.

Information Set, Expectations and Timing. In addition to its own states a household's decision to adopt also depends on the adoption decision of other households in the village. Under private information a household forms expectations about the sanitation adoption behaviour of others based on the common knowledge information set $x_t = (x_{it}, x_{-it})$.[17] A household learns taste shock ε_i prior to making it's own choices, but other households' taste shock ε_{-it} remain unknown to i.

Assumption Common Information: *The state vector $x_t = (x_{1t}, x_{2t}, ..., x_{Nt})$ denotes the common knowledge information set at time t observable to all households that belong to the same village.*

Assumption Private Information: *The choice specific taste parameter ε_{it}^{d} are private information shocks and are assumed to be distributed i.i.d across households and time.*

Though a household receives instantaneous utility from its consumption choice in period t, it only enjoys utility from its sanitation decision in the following period. This is because it takes *time to build* a sanitation facility at home which results in a delay between when an adoption choice is made and when the facility can be used and enjoyed at home. Similarly, the level of sanitation coverage $\overline{k}_{t-1}$ which is a state observable to all households at the start of period t captures the impact of underlying externalities generated by the level of adoption up to period $t-1$.

Assumption Time to Build: *A household that chooses to adopt sanitation in period t may only realise gains from choice $d_{it} = 1$ in the following period.*

[16]In addition to the taste shock ε the econometrician also observes a noisy measure of income.

[17]Since the household problem is defined over its life-cycle, where choices are made over age a the state vector denoted by $x_{at} = (x_{it}, x_{-it}|a_{it})$ is used when describing the household problem, where x_{at} indexes the household $i's$ information set at age a.

Household Income. The earnings function is modelled as an exogenous process for the household unit.[18] The log earnings in the current period id given by:

$$\ln y_{it} = f\left(age_{it}, edu_i\right) + z_{it} + \xi_{it}$$
$$z_{it} = z_{it-1} + u_{it}, \quad u_t \sim N\left(0, \sigma_u^2\right) \tag{3.1}$$

where $f(\cdot)$ is a function of the age and education of the household head.[19] The permanent component follows an A.R.(1) process with variance σ_u^2 for innovations. While the measurement error shocks in income ξ_{it} are assumed to be identically distributed across time and households with mean zero and variance σ_ξ^2. See Appendix (C) for further details on specifications.

Budget Constraint. The main motive for asset accumulation in the model is to finance the purchase of a sanitation facility, insure future consumption against income fluctuations and respond to preference shocks. I assume a standard inter temporal budget constraint augmented for the cost of sanitation (*price*) to relate future assets to the current stock of asset A_{it}, income y_{it}, and consumption c_{it}.

$$A_{it+1} = R\left(A_{it} + y_{it} - c_{it} - price * \mathbf{1}\left[d_{it} = 1\right]\right) \tag{3.2}$$

All households in the same village face the same sanitation purchase *price* i.e., the cost of building sanitation at home.[20] The initial stock of assets for household i is assumed to equal $A_{i0} = A_0\left(edu_i\right)$. The real interest rate r, $R = (1 + r)$ is the rate at which a household saves and accumulates wealth.[21] Households are allowed to save and accumulate assets but are unable to borrow against their future income.

$$A_{it} \geq 0 \tag{3.3}$$

The exogenous borrowing constraint restricts households from holding debt at any age a and time t and thus affects the inter temporal allocation of resources over the lifetime. The constraint may bind for a liquidity constrained household that would otherwise borrow against future income to smooth consumption and/or to purchase sanitation. Given preferences, the constraint may differentially bind over consumption and sanitation adoption choices.

[18]The model does not include the employment decisions of the household head or other members. Each household observed in the data derives a collective annual income amongst all household members where the head is the primary earner.

[19]In northern India the role of household head is culturally assigned to eldest working male (female, if widowed) who is also the primary earner and/or highest educated member within the household. It is assumed that household heads acquire all relevant education by the age 20. Thus edu_i refers to the education level at $a_{it} = 20$ with no further evolution in education attainment.

[20]The model does not allow for dynamics or uncertainty in the price process.

[21]The real rate of interest is set to $r = 0.02$ based on an approximation from interest rate data over the past 50 years from the Reserve Bank of India (RBI)

Sanitation Coverage. Within a village the level of sanitation coverage is denoted by the average level of adoption and evolves according to:

$$\overline{k}_t = \overline{k}_{t-1} + \frac{1}{N}\sum_{j=1}^{N} d_{jt} \qquad j = 1, ..., N \tag{3.4}$$

where state $\overline{k}$ denotes the existing level of sanitation each period and $\sum_{j=1}^{N} d_{jt}$ is the sum of the adoption choices made by households in each period. The sanitation coverage $\overline{k}$ captures the level of externality generated by the cumulative actions of all households within the village.

3.2 Strategies and Utility

Strategies. The strategy space σ of each household consists of a tuple $\sigma_{it}(x_t, \varepsilon_{it}) = \left[\delta_{it}(x_t, \varepsilon_{it}), c_{it}^{o}(x_t.\varepsilon_{it})\right]$ where δ denotes the adoption decision rule and c^o denotes the policy function for consumption.[22] Let $\sigma_t = \{\sigma_{it}(x_t, \varepsilon_{it})\}_{i=1}^{N}$ be a set of strategy functions which are associated with a set of conditional choice probabilities ($CCPs$) for sanitation adoption $P^{\sigma_t} = \left\{p_i^{\sigma_t}(d_{it}|x_t)\right\}_{i=1}^{N}$ such that:

$$p_i^{\sigma_t}(d_{it}|x_t) = \int 1\{d_{it} = \delta_{it}(x_t, \varepsilon_{it})\}\, g(\varepsilon_{it})\, d\varepsilon_{it} \tag{3.5}$$

which represents the expected adoption behaviour of household i from the point of view of other households $-i$, when household i follows strategy profile σ_{it} and other households follow σ_{-it}, and $\sigma_t = [\sigma_{it}, \sigma_{-it}]$ denotes a strategy profile. The choice probability is conditioned on all relevant observable information summarized by x_t at time t.

Expected Utility and Transitions. Each household maximizes its expected utility given expectations about the level of adoption. Let $u_i^{\sigma_t}(d_{it}, c_{it}, x_t)$ denote household $i's$ expected utility from choosing alternative d_{it} while other households follow σ_t.

$$u_i^{\sigma_t}(d_{it}, c_{it}, x_t) = \sum_{d_{-i}} u_i\left(d_{it}, c_{it}, \overline{d}_{-it}, x_{it}\right)\left(\prod_{j\neq i} p_j^{\sigma_t}(d_{-i}[j]|x_t)\right) \tag{3.6}$$

$$f_i^{\sigma_t}(x_{it+1}|x_t, d_{it}, c_{it}) = \sum_{d_{-i}} f_i\left(x_{it+1}|x_{it}, d_{it}, c_{it}, \overline{d}_{-it}\right)\left(\prod_{j\neq i} p_j^{\sigma_t}(d_{-i}[j]|x_t)\right) \tag{3.7}$$

where $f_i^{\sigma_t}(x_{t+1}|x_t, d_{it}, c_{it})$ is the transition probability of x conditional on household i choosing d_{it} given strategy σ_t.

[22] The policy function for the optimal consumption $c_{it}^{o}(x_{it};\sigma_t)$ is given by the maximization of the household problem described in the next section.

Preferences. A household derives utility from consumption c_{it}, state of adoption k_{it-1} and the level of sanitation coverage $\bar{k}_{t-1}$ and evaluates the benefits from sanitation against the cost of purchase. The per period utility for household i below the age $a < \mathcal{A}$ at time t is specified as:

$$u\left(c_{it}, d_{it}, x_{it}, \varepsilon_{it}^{d}; \theta\right) = c_{it}^{\nu}\left[1 + \eta k_{it-1} + \phi \bar{k}_{t-1}\right] + \alpha_{age_i} s\left(age_i, k_{it-1}\right) + \gamma k_{it-1}\bar{k}_{t-1} + \varepsilon_{it}^{d} \tag{3.8}$$

The private preference for sanitation ε_{it}^{d} enters as an additively separable shock. The first term on the right hand side of Equation (3.8) represents individual utility from consumption (c_{it}) and parameter $1-\nu$ denotes the coefficient of relative risk aversion. A household also enjoys direct utility from having sanitation at home in the form of convenience and other salient benefits, captured by α_{age} which may vary by the age of household head.[23] The non-separability between sanitation and consumption choice is captured by parameter η. Interacting the utility from consumption with adoption status captures potential complementarities that arise from sanitation adoption that improves latent health status and increases utility from food consumption. In addition to private convenience a household also derives additional benefits from the level of sanitation coverage. For example, a household may derive health benefits from residing in a village with a higher level of sanitation coverage and thus a lower degree of environmental pollution. Sanitation coverage level $\bar{k}_{t-1}$ denotes the fraction of households who have adopted sanitation by the end of the last period. The level of adoption in a village affects an individual household's utility through it's own adoption status captured by γ as well as through the impact on private consumption denoted by ϕ. The utility function $u(\cdot) \to -\infty$ for $c_{it} < 0$ which restricts adoption for households whose present cash-in-hand does not cover the cost of purchase i.e., $A_{it} + y_{it} < price * \mathbf{1}\left[d_{it} = 1\right]$. The preference specification reflects the *time to build* assumption where utility for i in period t depends on $\left(c_{it}, k_{it-1}, \bar{k}_{t-1}\right)$ instead of present choice d_{it}.

Since the adoption decision is a function of the sanitation prevalence within a village, aggregate village level characteristics may also affect the utility from sanitation and thus are an important feature to incorporate. For example, households in villages with drainage infrastructure and piped water supply are collectively more likely to adopt, and these villages are also where the existing sanitation coverage is high compared with villages with no drainage or water supply. To capture unobservable group level effects, I allow for a village specific 'fixed effect' by allowing the the location parameter μ(mean) of the taste shock ε_{it} to vary across villages. These location parameters act like 'fixed effects' capturing the impact of village specific characteristics not explicitly modelled or observed by the econometrician.[24] Under discrete choice, only the relative flow utility of sanitation adoption relative to non-adoption are identified and the parameter μ_g shifts this difference in values across villages.

[23] A report from the World Bank noted that female members of the household also enjoy a degree of personal safety from having a sanitation facility at home. The outside alternatives e.g. open fields or public sanitation facilities are associated with a higher degree of risk to personal safety especially for women.

[24] This modelling assumption allows me to relax the independence of ε shocks across households within a village in a specific way which yields as estimable parameter without loosing the tractability of the structure under the *i.i.d* assumption. Details on the variation in the data that identifies μ are discussed in the following section.

3.3 Household Problem

Households are forward looking and make decisions so as to maximize the present discounted value of the expected future utility subject to a set of constraints: (3.1),(3.2),(3.3) and (3.4). At each age from $a = 20 - 75$ a decision making household who is alive at time t chooses how much to consume c_{it} and save for the future. In addition, households that have not adopted sanitation $k_{it-1} = 0$, also choose whether or not to adopt d_{it} after observing their current period cash-in-hand, given cost of adoption (*price*) and level of sanitation coverage $\overline{k}_{t-1}$.

Using the Bellman principle, the dynamic problem of maximizing the expected lifetime utility under a given strategy σ_t can be formulated as:

$$V_i\left(x_t;\sigma_t\right) = \int \max_{d_{it}\in\mathcal{D}_{it}, c_{it}\in\mathcal{C}_{it}} \left\{ v_i^{\sigma_t}\left(d_{it}, c_{it}, x_t\right) + \varepsilon_{it}^{d} \right\} g\left(\varepsilon_{it}\right) d\varepsilon_{it} \tag{3.9}$$

The function V_i denotes $i's$ ex-ante value or Emax function which reflects expected utility at the beginning of the period before private shocks are realized. While $v_i\left(\cdot;\sigma_t\right)$ denotes the choice-specific value functions:

$$v_i\left(d_{it}, c_{it}^{o}, x_t;\sigma_t\right) = \max_{c_{it}\in\mathcal{C}_{it}} u_i^{\sigma_t}\left(c_{it}, d_{it}, x_{it}\right) + \beta \underbrace{\sum_{d_{-it}} \sum_{x_{t+1}} V_i\left(x_{t+1};\sigma_{t+1}\right) f_i\left(x_{it+1}|x_{it}, d_{it}, c_{it}, \overline{d}_{-it}\right) \left(\prod_{j\neq i} p_j^{\sigma_t}\left(d_{-i}\left[j\right]|x_t\right)\right)}_{\sum_{x_{t+1}} V_i(x_{t+1};\sigma_{t+1}) f_i^{\sigma_t}(x_{it+1}|x_t, d_{it}, c_{it})}$$

where β is the discount factor and the expectation is over realizations of future states, choices and shocks given the information set available to the household at time t. Also, $f_i^{\sigma_t}\left(x_{t+1}|x_t, d_{it}, c_{it}\right)$ denotes the expected transition probability of observable states x conditional on household i choosing $\left(c_{it}, d_{it}\right)$ integrated over the expected adoption decisions of other household $j \neq i$. Households make decisions until terminal age $\mathcal{A}$ with $V\left(x_t, \varepsilon_{it}|a_{it} = \mathcal{A}, \sigma_t\right) = 0$.

Adoption Decision Rule. The household decision rule for sanitation adoption is given by:

$$\delta_{it}\left(x_t, \varepsilon_{it};\sigma_t\right) = \begin{cases} 1 \quad if \quad v_i\left(d_{it}=1, c_{it}^{o}, x_t;\sigma_t\right) - v_i\left(d_{it}=0, c_{it}^{o}, x_t;\sigma_t\right) - \mu_g \geq \varepsilon_{it}^{0} - \varepsilon_{it}^{1} \\ 0 \quad if \quad v_i\left(d_{it}=1, c_{it}^{o}, x_t;\sigma_t\right) - v_i\left(d_{it}=0, c_{it}^{o}, x_t;\sigma_t\right) - \mu_g < \varepsilon_{it}^{0} - \varepsilon_{it}^{1} \end{cases} \tag{3.10}$$

Consumption Policy Function. The policy function for the optimal consumption is given by:

$$c_{it}^{o}\left(x_t;\sigma_t\right) = \arg\max_{c_{it}\in\mathcal{C}_{it}} \left\{ u_i^{\sigma_t}\left(d_{it}, c_{it}, x_{it}\right) + \beta \sum_{x_{t+1}} V_i\left(x_{t+1};\sigma_{t+1}\right) f_i^{\sigma_t}\left(x_{it+1}|x_t, d_{it}, c_{it}\right) \right\} \tag{3.11}$$

Solution. Given a strategy profile $\{\sigma_t\}$, a household's maximization problem can be cast as a finite horizon dynamic programming problem which can be solved via backward recursion from the terminal age $a = \mathcal{A}$. The solution to the household problem would be a function of the underlying strategy profile. However, to ensure consistency with the strategy played i.e., a household's expectation about sanitation prevalence and its future evolution are consistent, also requires the solution to a fixed point. The choice probabilities $p_i^{\sigma_t}(d_{it}|x_t)$ solve the coupled fixed point problem defined by:

$$V_i(x_t;\sigma_t) = \int \max_{d_{it}\in\mathcal{D}_{it}, c_{it}\in\mathcal{C}_{it}} \left\{ v_i^{\sigma_t}(d_{it}, c_{it}, x_t) + \varepsilon_{it}^d \right\} g(\varepsilon_{it})\, d\varepsilon_{it}$$

and

$$\Lambda_i(d_{it}|x_t;\sigma_t) = \int 1\left\{ d_{it} = \arg\max_{d_{it}\in\mathcal{D}_{it}} \left\{ v_i^{\sigma_t}(d_{it}, c_{it}^o, x_t) + \varepsilon_{it}^d \right\} \right\} g(\varepsilon_{it})\, d\varepsilon_{it}$$

Given a set of adoption probabilities $P^{\sigma_t} = \left\{ p_i^{\sigma_t}(d_{it}|x_t) \right\}_{i=1}^N$, the value functions $V_i(x_t;\sigma_t)$ are solutions to the N Bellman equations and the function $\Lambda_i(d_{it}|x_t;\sigma_t)$ denotes the best response probability function for each household i for a given strategy σ_t.

3.4 Equilibrium

Expectations over the adoption decisions of other households, conditional on observed states, allows an individual household to infer how the adoption coverage level will update in the next period. Since the time t states and expectations summarize all relevant information about other households in the village, a household's behaviour depends only on the current state x_t and own current private shock. An equilibrium under this markovian structure can be defined as follows:

The strategy profile $\sigma_t = (\sigma_{1t}, \sigma_{2t}, ..., \sigma_{Nt})$ is a Markov perfect equilibrium if and only if, given the opponents profile σ_{-it}, each household prefers the strategy σ_{it} to all alternative Markov strategies σ'_{it}. That is, σ_t is a MPE for all households i, at all states x_t and all alternative Markov strategies σ'_{it}.

$$V_i(x_t;\, \sigma_{it}, \sigma_{-it}, \theta) \geq V_i\left(x_t;\, \sigma'_{it}, \sigma_{-it}, \theta\right) \qquad \text{for all } i,\ x_t,\ \sigma'_{it} \tag{3.12}$$

A household's expected value under an alternative Markov profile σ'_{it} given states can be written recursively as:

$$V_i\left(x_t;\sigma'_t,\theta\right) = E_\varepsilon\left[u_i\left(\sigma'_{it}(x_t,\varepsilon_{it}), x_{it};\theta\right) + \varepsilon_i(d_i) + \beta\int V_i(x_{t+1};\sigma,\theta)\, f\left(x_{t+1}|x_t, \sigma'_{it}(x_t,\varepsilon_{it}), \sigma_{-it}(x_t,\varepsilon_{-it})\right) dx_{t+1}|x_t\right]$$

Existence of this equilibrium is a direct consequence of the finite horizon and finite action-space following Maskin & Tirole (2001). Equation (3.12) describe a set of inequalities which form the moment conditions constructed in the estimation procedure in the following section.

Multiplicity of Equilibria. In general, there may exist more than one solution to the system of equations in Equation (3.12). The multiplicity of the equilibria arises due to the interdependence of household adoption decisions that are consistent with distinct levels of sanitation coverage in equilibrium. At this stage the model is incomplete without the specification of an equilibrium selection rule (ESR). This 'incompleteness' introduces a challenge with respect to the estimation of the model where without an ESR the objective function is not well defined. This further adds to the computational burden of having to repeatedly solve the model for all possible equilibria under the dual specification above, for each candidate vector of parameters. Even if it would be possible to solve for the entire set of equilibria there is still an open question about the underlying equilibrium selection rule played, on which observed behaviour does not provide any additional information. In order to move forward with the estimation of the model, I impose the following assumption on the observed data.

Assumption Equilibrium Selection (*Single MPE*): *The data observed is generated by a single Markov perfect equilibrium profile* σ.

Under this assumption there exists a $1:1$ mapping between the observed behaviour in the data and the structural objects of the model which is discussed further in the identification section below. The main assumption here is that for each village, the data is generated by the same Markov perfect equilibrium profile. In practice, I pool data from multiple villages in which case Assumption *Single MPE*, which requires for the equilibrium selection to be consistent across villages, can prove to be restrictive. The assumption that the data observed is generated from one of the possible equilibrium affects the estimation of the reduced form objects i.e., conditional choice probabilities ($CCPs$). In order to consistently estimate the $CCPs$, I divide the villages into subgroups based on village level observables and geographic proximity. The underlying assumption being that villages close in geographic distance and similar in village specific demographics may play the same equilibrium selection rule which is consistent within that subgroup of villages.

3.5 Identification

This section discusses the identification of the primitives of the model from the data.[25] Identification analysis seeks a mapping from the set of reduced form objects i.e., policy functions and choice probabilities, that are observed in the data, to back out the primitive structure of the model. Based on the insight from Hotz & Miller (1993), Magnac & Thesmar (2002) demonstrate the degree of under identification of a discrete choice single-agent model under conditional

[25] Existing work on identification of pure discrete choice models (Magnac & Thesmar 2002, Srisuma 2015, Bajari, Chernozhukov, Hong & Nekipelov 2009, Bajari, Hong, Krainer & Nekipelov 2010) provides a useful starting point for analysing the model, but given the continuous choice, additional consideration is needed to find conditions for identifying the primitives of interest. The identification arguments follow from a combination of Magnac & Thesmar (2002) and Blevins (2014) which is amended to incorporate the additional strategic interaction element of the model. The constructive approach highlights the identifying power of each individual assumption and source of variation in the data.

independence by showing that, in general, fixing the discount factor $\beta < 1$, distributions of the taste shock $G(\cdot)$ and the utilities $u(\cdot)$ and terminal value in $V_t(d = 0|a = \mathcal{A})$ in one feasible alternative is just enough for identification for the remaining structure, i.e., transition probabilities $f(\cdot|x, d, c)$ and the utility function $u(\cdot)$.[26] Appendix (B) provides an exposition of their approach in the context of this model which also includes a continuous choice.

Exclusion Restriction. The strategic interaction component raises Manski's (1993) well known *reflection* problem of identification. Under the *reflection* problem it is hard to differentiate between whether group behaviour affects individual outcomes or instead group behaviour is simply an aggregation of individual actions. In order to identify the primitive utility of interest I impose exclusion restrictions. The expected choice-specific utility function is defined as:[27]

$$\underbrace{u_i^{\sigma}(d_i, c_i, x)}_{known} = \sum_{d_{-i}} u_i\left(d_i, c_i, \overline{d}_{-i}, x_i\right) \underbrace{\left(\prod_{j \neq i} p_j^{\sigma}(d_{-i}[j]|x)\right)}_{observed} \quad \text{for } i = 1, ..., N \tag{3.13}$$

In this system $u_i^{\sigma}(d_i, c_i, x)$ and the vector of choice probabilities $\{p^{\sigma}\}$ can be treated as known for all households.[28] Identification requires to find a unique set of structural payoffs $u_i\left(d_i, c_i, \overline{d}_{-i}, x_i\right)$ that solves this system of equations. A necessary condition for identification is that there are at least as many equations as free parameters $u_i^{\sigma}(d_i, c_i, x)$. The exclusion restriction implies that $u_i\left(d_i, c_i, \overline{d}_{-i}, x_i\right) = u_i\left(d_i, c_i, \overline{d}_{-i}, x\right)$ depends only on x_i, where $x = (x_i, x_{-i})$. Essentially, it is possible to find a set of covariates x_i that only shift the utility of household i independently of the payoff functions of the other households.

Assumption Exclusion Restrictions (*Excl Rest*): *The states x_{-i} of other decision making households are included in the information set of household i on which expectations on adoption decision p_{-i} are formed but are excluded from i's payoff function*

Without this partition of the state vector in Equation (3.13), for a fixed x, there are $N \times N$ unknowns[29] corresponding to the $u_i^{\sigma}(d_i, c_i, x)$ after imposing the normalization on a reference alternative.[30] However, there are only N equations which implies that without additional restrictions, the structural parameters are not identified. By partitioning the state vector where x_{-i} enters the probability function $p_{-i}(d_{-i}[j]|x_i, x_{-i})$ but is excluded from $u_i\left(d_i, c_i, \overline{d}_{-i}, x_i\right)$.

[26] The structure of the model is defined by $s = \{u_i(\cdot), f(\cdot), G, \beta\}$. In what follows, I treat both the transition functions and distribution $G(\cdot)$ as known and consider identification of the utility functions. Blevins (2014) also considers nonparametric identification of the distribution of unobservables.

[27] For ease of exposition time subscript is subsumed.

[28] Appendix (B) shows how $u_i^{\sigma}(d_i, c_i, x)$ is identified from the observed data.

[29] In this model where only the average level of adoption enters the utility the degree on under identification is less but still positive with $N \times N$ unknowns, instead of $N \times 2^{N-1}$ unknowns if the identity of the households would matter.

[30] For all $d_{-i} \in D_{-i}$ and all x, $u_i\left(d_i = 0, c_i, \overline{d}_{-i}, x_i\right) = 0$ which also implies $u_i^{\sigma}(d_i = 0, c_i, x) = 0$. I impose this assumption by normalizing per period flow utility from non-adoption to zero. This normalization must hold for any strategy d_{-i} that could be used by other households and for each value of the state variable x.

Holding x_i fixed and varying x_{-i} it is possible to increase the number of equations that $u_i\left(d_i, c_i, \overline{d}_{-i}, x_i\right)$ must satisfy. If there are at least N points of support of the conditional distribution of x_{-i} given x_i it is possible to generate more equations than free parameters.

The intuition behind how exclusion restrictions generate identification is as follows. In the model, the state vector $[A_{-it}, y_{-it}]$ which denotes the cash-in-hand for households $(-i)$ does not directly affect the utility that household i derives from it's sanitation choice. Along this space, the variation of assets and income of other households' will perturb the adoption probability p_{-i} but leaves $i's$ utility unchanged. This variation shifts the equilibrium strategy of household $-i$, leaving the components of household $i's$ payoff from adoption fixed. Based on the *reflection* problem, the exclusion restriction allows for exogenous variation in the group behaviour thus isolating the impact of aggregate behaviour on individual outcomes.[31]

Identification of preference parameters and village shocks. This section discusses how specific elements of the state transitions and flow utility are identified from the empirical moments. In the data, each period t choice and state combination implies a probability distribution over period $t+1$ states and these moments identify parameters that govern state-to-state transitions $\mathrm{f}(\cdot)$, including those for the income earnings function.

Parameter vector θ in the flow utility function[32] and the discount factor β are identified through observed state dependent choice distributions. The CRRA coefficient $1-\nu$, which measures the curvature in consumption utility function is identified using the state dependent asset accumulation distribution. The variation in the mean asset accumulation level by age of the household head traces out the marginal utility of consumption. In addition, the change in the asset accumulation (variance) across different age groups helps identify the degree of impatience denoted by the discount factor β.

Similarly, the variation in the proportion of adoption by age of the household head captures $\alpha\,(age)$. While variation in asset accumulation conditional on sanitation adoption status helps identify η. Across village variation in the sanitation coverage and asset accumulation conditional on adoption status provides identification of parameters that govern the impact of the externality γ and ϕ. The exclusion restriction provides exogenous variation in the sanitation coverage across villages. Unobserved group effects are identified by observing the aggregate adoption choice within a village that is consistently different from the choice distribution in another village given the same set of states. Thus the residual variation from the adoption and asset accumulation distribution of households conditional on coverage levels across villages identifies village level fixed effects denoted by the location (mean) parameter of the taste shock μ_g.

[31]Given the continuous nature of exclusion restriction state variables $x_{-i}$with a rich support, the model is over identified. This implies that in principle the model can be rejected by the data.

[32]utility function parametrized by $\theta = \left[\nu, \eta, \phi, \alpha\,(age), \gamma, \mu_g\right]$where μ_g denotes mean of the taste shocks capturing village level fixed effects.

4 Estimation

The model is estimated using a two step procedure that closely follows Bajari, Benkard & Levin (2007)[33] which extends the simulation based two-step approach of Hotz, Miller, Sanders & Smith (1994) to the estimation of dynamic games. In addition to the standard discrete choice, BBL (2007) also allows for continuous choices. The estimation is divided into two steps. In the first step, I recover the household's policy functions for adoption and consumption, along with estimates for the state transitions. Under rational expectations, households are assumed to have correct expectations about their environment and the behaviour of other households. As a consequence, by estimating the probability distributions for decisions and states, under the $Single\,MPE$ assumption, I effectively recover a household's equilibrium expectation for sanitation adoption in the first stage. In the second stage, I recover the structural parameters that rationalize the observed equilibrium choices as a set of optimal decisions. Following BBL (2007), the conditions for optimality are represented as a system of inequalities that require each household's observed behaviour to be weakly preferred to feasible alternatives at each state.

In this section, I describe the estimation procedure undertaken which differs from BBL (2007) in the first stage. The key difference is the way in which the policy function for the continuous consumption choice is obtained. The approach can be viewed a hybrid of a two-step and full solution method to accommodate the challenges that arise with limited data size.[34] Instead of estimating the policy function of consumption off the observed data, I instead incorporate the single-agent (SA) model dynamic programming numeric solution to back out the consumption (or savings) policy function. This is discussed in further detail below.

4.1 First-stage: Policy Functions & State Transitions

Decision Rule. The decision rule for sanitation adoption in Equation (3.10) is a function of the choice specific value functions $v\left(d_{it}, c^{o}_{it}, x_t; \sigma_t\right)$. Using the Hotz and Miller (1993) inversion it is possible to recover the choice specific value functions by inverting the observed choice probabilities at each point in the state space. Under the Type 1 extreme value distribution assumption on the taste shocks the inversion takes the familiar form for a binary discrete choice:

$$v_i\left(d_{it}=1, c^{o}_{it}, x_t; \sigma_t\right) - v_i\left(d_{it}=0, c^{o}_{it}, x_t; \sigma_t\right) - \mu_g = \ln\left[p_i\left(d_{it}=1|x_t\right)\right] - \ln\left[1 - p_i\left(d_{it}=1|x_t\right)\right]$$

[33] From now on referred to as BBL (2007)

[34] Under a full solution approach, each household's dynamic problem is numerically solved at all possible states subject to the fixed point equilibrium condition to obtain the policy functions. The two-step procedure bypasses the computational burden associated with solving the model, by directly estimating the policy function off the conditional variation in the choices observed in the data. Though the two-step eases the computational burden it instead places a burden, especially with continuous choice, on the amount of observations required to consistently estimate policy functions from the variation in the data.

It is sufficient to recover the difference in the choice-specific value functions to recover the decision rule:

$$\widehat{\delta}_{it}\left(x_t, \varepsilon_{it}; \sigma_t\right) = \begin{cases} 1 & if \quad \ln\left[\widehat{p}_i\left(d_{it}=1|x_t;\widehat{\psi}\right)\right] - \ln\left[1-\widehat{p}_i\left(d_{it}=1|x_t;\widehat{\psi}\right)\right] \geq \varepsilon^0_{it} - \varepsilon^1_{it} \\ 0 & if \quad \ln\left[\widehat{p}_i\left(d_{it}=1|x_t;\widehat{\psi}\right)\right] - \ln\left[1-\widehat{p}_i\left(d_{it}=1|x_t;\widehat{\psi}\right)\right] < \varepsilon^0_{it} - \varepsilon^1_{it} \end{cases}$$

where $\widehat{p}_i\left(d_{it}=1|x_t\right)$ is an estimate of the choice probability of adoption conditional on the state variable x_t and $\widehat{\psi}$ denotes a vector of first stage parameters employed in the estimation of the choice probabilities. In general the estimation of conditional choice probabilities (CCPs) would require a fairly flexible specification. However, with a state space that includes continuous variables and restricted sample size, flexibility is difficult to achieve in practice. In addition, the CCP estimates are divided into groups based on village level observables and geographic proximity to account for the underlying equilibrium selection rule. Table (7) in the appendix provides first stage CCP estimates.

Consumption Policy Function. In principle, the consumption (or savings) policy function is directly estimable from the observed distribution of consumption (or saving) conditional on the adoption decision.[35] However, to obtain consistent estimates for either consumption or savings from observed conditional variation makes further demands from the existing dataset on the amount of observations within each state partition cell. Instead, I propose to solve for the consumption policy function using the numeric solution for a single-agent dynamic problem.

Hybrid. Given that the strategic element is with respect to the sanitation decision and the consumption decision is affected indirectly through adoption it is possible to decompose the model into smaller individual maximization problems. This parallels the second feature of equilibrium models, namely that household's maximize expected discounted utility given their expectations about the decisions of other households and the evolution of the relevant states.

A point of note is that the hybrid procedure follows naturally from the structure of the model which allows me to divide it into smaller parts. Conditional on the probability of adoption the model can be viewed as a single agent dynamic programming problem which can be estimated using a variety of standard techniques such as the nested fixed point approach Rust (1997). Instead of fully solving the model given the fixed point, I only solve an individual household's problem conditional on the strategy played in the village. Given expectations on the adoption decision of other households, an individual household solves its own life-cycle problem of sanitation adoption and consumption.

The single-agent sanitation adoption and consumption problem is solved at all possible state realizations. The initial conditions are imputed from the observed data at age $a = 20$. The solution also builds the evolution of the deterministic state transition functions. The inter temporal budget constraint governing asset stock evolution depends on the consumption and adoption decisions made. Both the budget constraint and the liquidity constraint faced by an individual household

[35] Provided that, for all adoption choice and states, the policy function $c^o\left(x, \xi\right)$ is strictly increasing in the measurement error shock in income ξ. Under this monotonicity assumption, the policy function c^o provides a $1:1$ mapping from the space of shocks $\xi \in \mathcal{K}$ to the space of continuous consumption choice $\mathcal{C}$ for all adoption choices and states. For additional details refer to Appendix (B)

are built into the SA solution which determines the optimal consumption and saving policy at each point in the state space.

Exogenous State Transitions. The income process described in Equation (3.1) is estimated directly from the observed data. Income is modelled to be a function of age, education and education-squared. Table (5) lists the parameter estimates for the income process. Income increases with human capital (as measured by education) but at a decreasing rate. Age effects vary, with lower wage predicted for households with older household heads.

Evolution of Sanitation Coverage. In addition, the SA solution is also solved over a grid of sanitation coverage states $\overline{k}$ at all points. I discretize the realizations of sanitation prevalence over a 100 grid points in the numeric solution. The law of motion for sanitation coverage within a village $\overline{k}$ is generated/determined in conjunction with the forward simulation procedure in the next stage. I also assume that an individual household's adoption choice today (t) has an infinitesimal change on the level of sanitation prevalence tomorrow ($t+1$) given that households interact in relatively large village groups.

4.2 First-stage: Value Functions

The first stage estimates of the policy and transition functions are used to construct estimates of the value functions which form the moment conditions employed in the second stage. A forward simulation procedure is used to estimate the ex-ante value function $V_i\left(x_t;\sigma_t,\theta\right)$ for each household i at state x_t. The procedure allows me to obtain an estimate of the value functions for different strategy profiles σ_t given a parameter vector θ. A single simulated path is obtained as follows:[36]

$$\widehat{V}_i\left(x_t;\sigma,\theta\right)=\frac{1}{S}\sum_{s=1}^{S}\sum_{\tau=t}^{T=\mathcal{A}}\beta^{\tau}u_i\left(x_{\tau},\sigma_{\tau}\left(x_{\tau},\varepsilon_{\tau s}\right);\theta\right)+\varepsilon^{d}_{i\tau s}$$

1. Starting at state $x_0=x_t=\left(x_{it},x_{-it}\right)$
2. Draw private shocks ε_{i0s} from the distribution $G_i\left(\cdot\right)$ for each household i
3. Using the policy function estimate $\widehat{\sigma}_i\left(x_0,\varepsilon_{i0};\psi_1\right)=\left[\widehat{\delta}_i\left(x_0,\varepsilon_{i0};\psi_{11}\right),\widehat{c}^{o}_i\left(x_{i0};\psi_{12}\right)\right]$ compute the specified choices $\left(d_{i0},c^{o}_{i0}\right)$ for each household i and the resulting per period utility $u_i\left(d_{i0},c^{o}_{i0},x_{i0};\theta\right)+\varepsilon^{d_{i0}}_{i}$
4. Using the estimated transition functions $\widehat{f}\left(\cdot|d_{i0},c^{o}_{i0},x_0,\psi_2\right)$ draw a new state x_1 for each one of the households i and move forward to the next period
   - **Hybrid:** The evolution for $\overline{k}$ is determined by aggregating the adoption decisions for all households, $\overline{k}_1=\overline{k}_0+\frac{1}{N}\sum_i d_{i0}$

[36] The forward simulation to construct V_i for each household is performed village by village using the relevant conditional choice probability estimates.

5. Forward simulation entails repeating steps 2-4 for each household i, $t = T$ periods forward i.e., till each household reaches terminal age $\mathcal{A}$

6. Steps 1-5 generates a single path of play for each one of the households

7. The entire process is repeated for S draws of shocks and average i's discounted sum of utilities over the S simulated paths.

Averaging over the S simulated paths gives an estimate $\widehat{V}_i$ for the value function $V_i(x_t; \sigma_t, \theta)$. Such an estimate can be obtained for any (σ, θ) pair, including the $(\widehat{\sigma}, \theta)$ where $\widehat{\sigma}$ is the policy estimate from the first-stage estimation. It follows that $\widehat{V}_i(x; \widehat{\sigma}, \theta)$ is an estimate of household $i's$ sum of discounted utility from $\widehat{\sigma}_i$ given the strategy of other households $\widehat{\sigma}_{-i}$, where $\widehat{\sigma} = (\widehat{\sigma}_i, \widehat{\sigma}_{-i})$

4.3 Second-stage: Structural Parameters

The second stage combines first stage estimates with the necessary conditions for equilibrium from the model, to recover the structural parameters that rationalize the observed policies as a set of optimal decisions. The equilibrium inequalities in Equation (3.12) define a set of parameters that rationalize the underlying strategy profile σ as a Markov perfect equilibrium (MPE) of the game.[37] Under the assumption of $Assump : Single\, MPE$ and $Assump : Excl.\, Rest$ the second stage estimator discussed in BBL (2007) yields standard point estimates of the parameters. Following the notation of BBL (2007) I define an equilibrium condition as:

$$g_i\left(\left(i,\, x,\, \sigma_i'\right)_\lambda; \theta, \psi\right) = V_{i(\lambda)}\left(x_{(\lambda)}; \sigma_i, \sigma_{-i}, \theta, \psi\right) - V_{i(\lambda)}\left(x_{(\lambda)}; \sigma_{i(\lambda)}', \sigma_{-i}, \theta, \psi\right)$$

where $\lambda \in \Lambda$ indexes the equilibrium conditions denoted by a combination $\left(i,\, x,\, \sigma_i'\right)$. Each inequality indexed by λ is satisfied at θ, ψ if $g_i\left(\left(i,\, x,\, \sigma_i'\right)_\lambda; \theta, \psi\right) \geq 0$. The model's parameters are estimated as the solution to this system of inequalities by employing a minimum distance estimator that minimizes violations of these optimality conditions. The objective function that is minimized is given by:

$$Q(\theta, \psi) = \int \left(\min\left\{g\left(\left(i,\, x,\, \sigma_i'\right)_\lambda; \theta, \psi\right), 0\right\}\right)^2 dH(\lambda)$$

where $H(\cdot)$ is the distribution over the set Λ of inequalities.[38] Under the assumptions that ensure the model is point identified and that $H(\cdot)$ has a sufficiently large support, $Q(\theta, \psi) > 0$ for all $\theta \neq \theta_0$. Parameter θ is estimated by minimizing the sample analogue of the objective function at $\psi = \widehat{\psi}$.[39]

[37] BBL(2007) denote Θ_0 as the set:

$$\Theta_0(\sigma, f) := \left\{\theta : \theta,\, \sigma,\, f \text{ satisfy (3.12) for all } x,\, i,\, \sigma_i'\right\}$$

The goal of the second stage is to recover Θ_0 using the first stage estimates of the policy functions σ and transitions functions f. Depending on the model and its parametrization, the set Θ_0 may or may not be a singleton.

[38] The true parameter vector θ_0 satisfies $Q(\theta_0, \psi_0) = 0 = \min_{\theta \in \Theta} Q(\theta, \psi_0)$ where Θ contains θ_0.

[39] The Nelder Mead algorithm was employed to minimize the objective function. Monte Carlo simulations were performed using simulated data to understand the properties of the BBL (2007) estimator.

$$Q_n\left(\theta,\widehat{\psi}\right) := \frac{1}{n_I}\sum_{k=1}^{n_I}\left(\min\left\{\widehat{g}_i\left(\left(i,\,x,\,\sigma'_{i(k)}\right)_{\lambda_k};\theta,\widehat{\psi}\right),0\right\}\right)^2$$
$$\widehat{\theta}\;\arg\min_{\theta\in\Theta} Q_n\left(\theta,\widehat{\psi}\right) \tag{4.1}$$

where $\widehat{g}_i\left(\cdot\right)$ is the empirical counterpart to $g\left(\cdot\right)$

$$\widehat{g}_i\left(\left(i,x,\sigma'_{i(k)}\right)_{\lambda_k};\theta,\widehat{\psi}\right) = \widehat{V}_{i(\lambda)}\left(x_{(\lambda)};\widehat{\sigma}_i,\widehat{\sigma}_{-i},\theta,\widehat{\psi}\right) - \widehat{V}_{i(\lambda)}\left(x_{(\lambda)};\sigma'_{i(\lambda_k)},\widehat{\sigma}_{-i},\theta,\widehat{\psi}\right)$$

By constructing empirical counterparts to all or a subset of the equilibrium inequalities using the forward simulation procedure described in section (4.2) the idea is to search for values of θ that minimizes the violations of these inequalities. Standard errors are computed using a bootstrap procedure. Further details are provided in Appendix (C).

4.4 Parameter Estimates

The model has a total of 74 parameters. I focus here on a subset, in particular on the estimates describing preferences obtained in the second stage in Table (2).[40]

Table 2: Structural Estimates: Preference Parameters

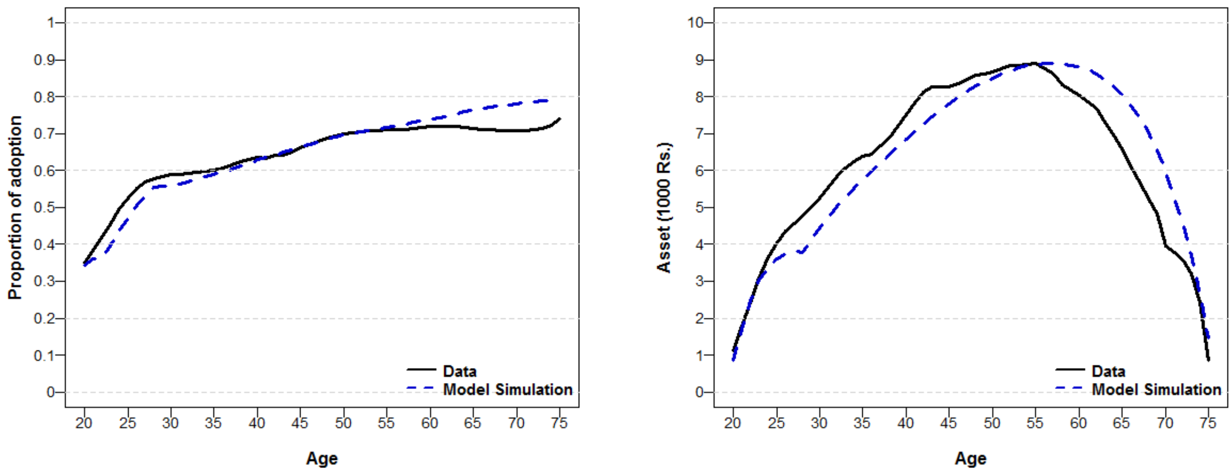
Parameter	**Estim.**	**Std Err.**	**Description**
ν	0.3376	(0.026)	$(1-\nu)$ coeff of rel. risk aversion
η	0.00022	(0.0001)	interaction c_t & own sanitation
ϕ	0.00514	(0.002)	interaction c_t & average sanitation prev.
$\alpha_{20\leq a<26}$	4.8155	(0.092)	importance of sanitation at 20≤age<26
$\alpha_{26\leq a<75}$	0.0138	(0.002)	importance of sanitation at 26≤age<75
γ	2.7019	(0.024)	interaction own sanitation & average sanitation prev.
β	0.9436	(0.014)	discount factor

Notes: Model parameters characterizing preferences and discount rate. Bootstrap standard errors computed using 250 bootstrap resamples. Calibrated values: $r = 0.02$ real interest savings rate based on data from the *Reserve Bank of India* (RBI).

Utility in the model is derived from consumption and having sanitation at home. Everything else equal, households derive higher utility from having sanitation at home with the differential effects based on the age of the household head. The estimate of ν indicates a decreasing marginal utility of consumption. While the parameter η indicates a marginally higher return derived from food/other consumption by having sanitation at home. Households also derive additional utility from the aggregate coverage of sanitation within the village. This effect is captured by the positive parameter estimates for γ and ϕ which capture the non-separable effect of average sanitation coverage on the additional gains a household derives from it own consumption and sanitation.

[40] A complete list of the parameters estimates is provided in Appendix (E), which includes first stage estimates in Tables (5) -(7) and the estimates for the village level fixed effects $\widehat{\mu}_g$ in Table (8).

Figure 2: Model Fit: Life Cycle Profiles



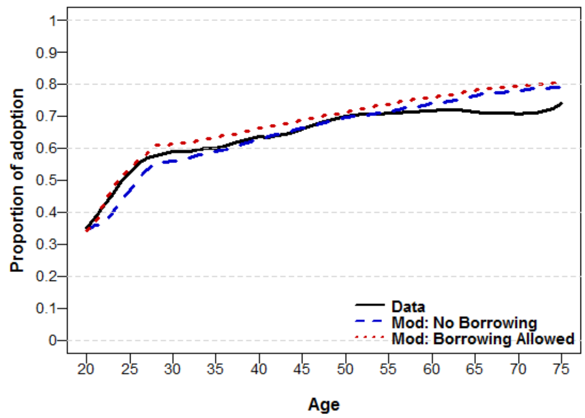
(a) Proportion of Sanitation Adoption

(b) Assets over the Life Cycle (1000 *Rs*.)

4.5 Model Fit

The fit of the model is evaluated along two dimensions: life cycle profiles and aggregate sanitation coverage observed in the data. The model closely matches the observed behaviour for sanitation adoption choices as well as asset accumulation over the life-cycle. Figure (2) plots the empirical and model generated profiles for the fraction of sanitation adoption (2.a) and mean assets (2.b) by age of the household head. The estimation procedure does not directly employ the empirical age profiles as moments in the estimation of the structural parameters and thus the fit can be viewed as one 'non targeted' moments. Overall the model replicates household behaviour over the life cycle in terms of sanitation adoption fairly well. There exists discrepancy at older ages, the model predicts higher adoption levels than observed in the data past the age of 55. Additional discussion of the model fit with respect to the sanitation coverage across villages observed in the data is included in Section (5.2).

Figure 3: Impact of Liquidity Constraints



Impact of Liquidity Constraints. As a robustness check, I also look at how the simulated sanitation adoption behaviour would change if the underlying model were to be re-estimated without restricting households from borrowing against their future income. I re-estimate the model where under the forward simulation procedure differently from before I allow households to have negative asset holdings (debt) based on optimization of their consumption and sanitation choice subject to the natural borrowing constraint and terminal age conditions.[41] The re-estimated preference parameters are provided in Table (6) in the appendix.

Figure (3) plots the simulated sanitation adoption profile under the re-estimated model along with the empirical profile. Under relaxation of the liquidity constraints the model simulation predicts a marginal increase in the proportion of sanitation adoption at each age. Though small, the gap between the two model generated profiles decreases with age. This is driven by the model feature where conditional on not being liquidity constrained households find it optimal to adopt sanitation earlier rather than later in life so as to enjoy the utility from sanitation over a longer time horizon. The maximum difference between the two simulated profiles is less than 7 % and the profile generated under relaxed borrowing constraints is well within the 95 % confidence interval bounds estimated under the model with liquidity constraints. Overall, it is possible to conclude that the household sanitation adoption behaviour under the model where borrowing is fully restricted is robust under this assumption. Though the model where borrowing is fully restricted is taken as a good fit of the data, this exercise does not necessarily conclude that the observed households are indeed liquidity constrained, as the constraint $A_t \geq 0$ may not necessarily bind for all households. Further analysis of this issue is included with the counterfactual policy simulations in Section (6).

[41] Each household must leave terminal age $\mathcal{A}$ without debt i.e., $A_{\mathcal{A}+1} \geq 0$.

5 Simulation of Sanitation Adoption

In this section, I outline the simulation method to determine sanitation equilibrium levels under different counterfactual environments. Under single agent models the underlying assumption is that each household's outcome varies only with its own policy treatment. To accommodate the presence of externalities, I need to allow a household's outcome to also depend on the outcomes of other households impacted by the policy thereby allowing for multiple equilibria in counterfactual environments. In order to conduct counterfactual experiments in models with multiple equilibria, one approach would be to define the Equilibrium Selection Mechanism (ESM) and to compute the full set of equilibrium under estimated parameter values. However, even if it would be possible to compute the full set equilibria,[42] observed behaviour does not provide any additional guidance on the underlying equilibrium selection rule played.

Most examples in the literature instead impose an equilibrium selection rule ex-ante under which the model is both estimated and simulated for counterfactual policies. A key limitation of this approach is that it does not allow for the possibility that the equilibrium selection mechanism may itself change under counterfactual environments. Thus the policy simulation given a selection rule may not be valid under a different counterfactual environment.

My approach here differs, instead of solving and simulating for all possible equilibria I instead bound the set of possible equilibria by an upper and lower limit. To evaluate the effect of counterfactual policies on equilibrium sanitation prevalence, I focus on the resulting shifts in the upper and lower bounds based on changes to the underlying environment.[43] The approach of bounding the equilibrium set is appealing as it allows for changes in the underlying equilibrium selection rules played under counterfactual environments. However, a trade-off for this advantage is that it only allows one to bound the region where the impact of the policy may lie. If the estimated bounds under a policy simulation are too wide this would affect the precision of the policy implications derived.

5.1 Strategic Complementarity

To ascertain household behaviour under counterfactual policies, I propose the following approach. First, I characterize the conditions under which the model implies strategic complementarity in the adoption decisions. Specifically, I verify whether the household objective function displays the properties of a supermodular game with respect to the adoption decision, i.e., the household preferences satisfy *Increasing Differences* over the sanitation adoption dimension. Then I derive conditions under which such a condition is sufficient to ensure that

[42] Iskhakov, Rust & Schjerning (2016) propose an algorithm, *Recursive Lexiographic Search (RLS)* that attempts to solve for all Markov Perfect Equilibria for a class of Markovian Games that they define as *Directional Dynamic Games (DDG)*. The directional property of the game is defined over the stochastic evolution of certain state variables other than the passage of calendar time or age. Under certain conditions the model in this paper also satisfies directionality in the evolution of the sanitation coverage within a village.

[43] The idea of bounding the equilibrium set has previously been employed by Jia (2008), De Paula (2009) and Bjorkegren (2014) in different contexts to solve and simulate the model under multiple equilibria.

the set of equilibria satisfies the ordinal properties that characterize supermodular games, i.e. there is a highest and a lowest pure strategy equilibrium with respect to a household's sanitation adoption. I then exploit the properties of such a structure to characterize the upper and lower bound of the equilibrium sanitation adoption level at village level. The interpretation of the bounds obtained under the iteration procedure depends the properties of the model described in this paragraph. The approach extends a traditional result of supermodular games by employing a notion of separability of the objective function over the choice set similar to Topkis (1978).[44] A detailed derivation of the result is provided in Appendix (D). The argument is arranged in three steps and is greatly simplified by the choice of timing employed in the model i.e., 'time to build' sanitation.

The intuition behind the main result is as follows. If household sanitation adoption decisions are strategic complements, then a larger average level of adoption in the village makes adoption - *ceteris paribus* - more attractive for every household. This is the case if the household's objective function satisfies *Increasing Differences* with respect to the adoption decision. I prove that this condition is satisfied by the model under weak assumptions. On the other hand, a larger average level of sanitation adoption may change the trade-off of the consumption and saving decisions of a household and this may, in turn, affect household adoption decisions. I show that, if the parameter capturing the interaction between private consumption and average level of sanitation coverage in the village: ϕ is sufficiently close to zero, then the second channel vanishes. As a consequence, the existence of a highest and a lowest equilibrium with respect of household sanitation adoption is ensured. This result dramatically simplifies the counterfactual analysis, because in order to bound the set of equilibria of the game with respect to the average level of adoption in equilibrium it is sufficient to simulate bounds for two specific upper and lower equilibria.

5.2 Simulation Method

To compute the bounds for the set of equilibrium sanitation adoption levels, I use an iterated best response algorithm to search for the fixed points. As explained above the procedure does not attempt to recover all possible equilibria, but instead only the upper and lower limits characterizing the set of possible equilibria. The algorithm can be divided into two steps. I first construct a candidate adoption path using the forward simulation procedure described in section (4.2) under estimated parameter values. There are an initial set of households $\{k_{i0}\}_{i=1}^{N}$ who made their sanitation adoption decision before my data begins, I hold their decision fixed. For baseline simulations, the initial adoption level $\bar{k}_0$ is set equal to the sanitation level observed in the first period of the data, such that at the first step of the algorithm households expect the level of sanitation observed in the data.

In the second step, an iterative procedure is used on each candidate adoption path to obtain a fixed point. The index τ denotes an iteration. Each candidate adoption path and equilibrium identified depends on the initial adoption level $\bar{k}_0$ along with the vector of observed states and

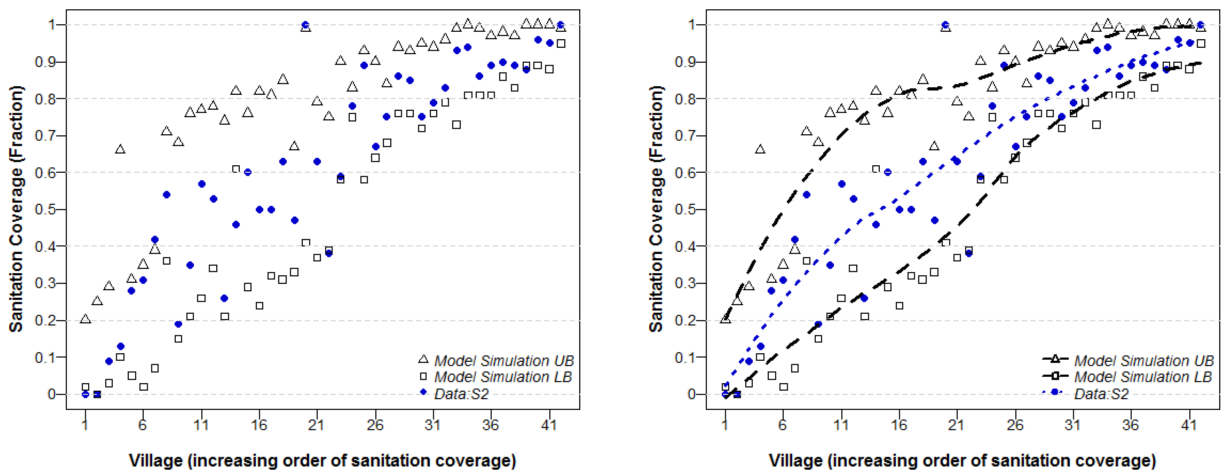
[44]Ref. Topkis (1978) Theorem (3.3)

taste shocks $\varepsilon = \{\varepsilon_{i0}\}_{i=1}^{N}$ drawn. To locate the lower and upper limits $\left(\bar{k}^{L}, \bar{k}^{U}\right)$, assumptions are imposed on the future adoption path of all households within a village. For the lower limit, I assume that each household i believes that the level of sanitation in each subsequent period until i reaches terminal age $\mathcal{A}$ remains at the initial level $\bar{k}_0$ under each iteration. Similarly for the upper limit, each household i believes that the level of sanitation in each subsequent period until $\mathcal{A}$ is close to $\approx 100\%$ coverage.

For the lower bound $\bar{k}^{L}$:

1. Under the assumption that the future level of adoption remains at observed $\bar{k}_0^{\tau=1}$ till terminal age $\mathcal{A}$ (given iteration $\tau = 1$)
2. Draw set of private taste shocks ε_{i0} for each household $i = 1, ..., N$ and allow each household to optimize their decision, holding fixed the adoption path of other households given assumptions about the future evolution of $\bar{k}$
3. Compute utility and choices (d_{it}, c_{it}) for each household i using the estimated policy and transitions functions
4. Forward simulate each household's choice problem until each household i reaches $\mathcal{A}$ terminal age
5. With each move one period forward update the sanitation level $\bar{k}$ by averaging over the adoption decisions for all households each period: $\bar{k}_1^{\tau=1}, \bar{k}_2^{\tau=1}, \bar{k}_3^{\tau=1}$ etc.
6. Continue forward simulation for each household updating the sanitation level $\bar{k}$ till $\bar{k}_M^{\tau=1} = 1.0$ i.e., all household have adopted and obtain a candidate adoption path denoted by vector $\overrightarrow{\bar{k}}^{\tau=1} = \left(\bar{k}_0^1, \bar{k}_1^1, ..., \bar{k}_M^1\right)$
7. Repeat steps 1-6 under the same ε_{i0} draws to obtain another candidate adoption vector $\overrightarrow{\bar{k}}^{\tau=2} = \left(\bar{k}_0^2, \bar{k}_1^2, ..., \bar{k}_M^2\right)$
   - Where initial $\bar{k}_0^{\tau=2}$ level (starting point) is obtained by computing the adoption decision rules for all households i under the assumption that $\overrightarrow{\bar{k}}^{\tau=1}$ is the relevant adoption path played.
8. Iterate, using the path from the previous step to form the next adoption path.
9. Repeat until $\overrightarrow{\bar{k}}^{\tau+1} = \overrightarrow{\bar{k}}^{\tau}$ i.e., the adoption path vector in each iteration converges to obtain the fixed point.
   - The first element of this convergent vector $\overrightarrow{\bar{k}}^{\tau+1}$ is obtained as the lower bound $\bar{k}^{L}$

Figure 4: Model Fit: Simulation by Village



Similarly for the upper bound $\bar{k}^U$ the convergent vector is obtained by repeating the process starting at the observed level of $\bar{k}_0$ but under the assumption that next period onwards the level of sanitation adoption is $\approx 100\%$. In this way the sanitation adoption path vector converges with each subsequent iteration. The first element of this convergent vector is obtained as the upper bound of the set. Since a candidate adoption path and the fixed point obtained is a function of ε_{i0} shock drawn the iteration procedure is repeated for multiple draws s of $\{\varepsilon_{i0s}\}_{s=1}^{S}$ and the lower and upper bounds are computed as the midpoints of the resulting distributions.[45]

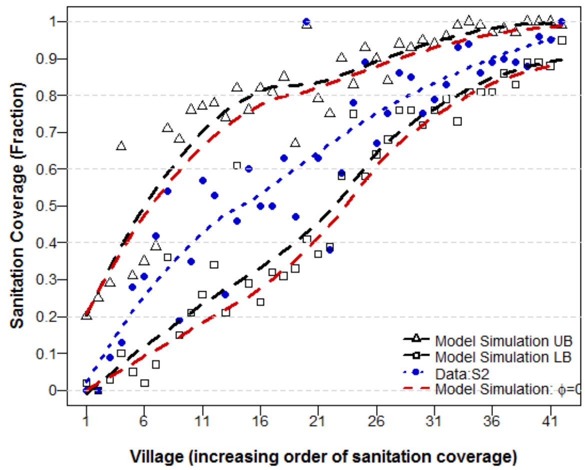
Baseline Simulation

Under the estimated model, I run the simulation procedure on the same environment as the data observed to get a sense of the model 'fit' at the aggregate village level. Using data from the first period the model is simulated one period forward for the predicted upper and lower bounds of the equilibrium level of sanitation. The upper and lower bound simulations are computed for each of the 42 village groups observed in the sample data. Figure (4) plots the model simulated bounds for the observed data points in period two *Data* : *S*2 of the sample panel where the horizontal axis denotes different villages in order of increasing sanitation prevalence.[46] Though the model simulated bounds are wide at certain points in most cases the sanitation prevalence observed in the data lies within the bounds predicted by the model.

[45]In practice, the iteration procedure is performed for 250 independent draws for the set of taste shocks ε.

[46]Table (10) in the appendix provides a complete list of the simulated bounds at baseline for the observed data in period two.

Figure 5: Model Fit: Model $\phi = 0$

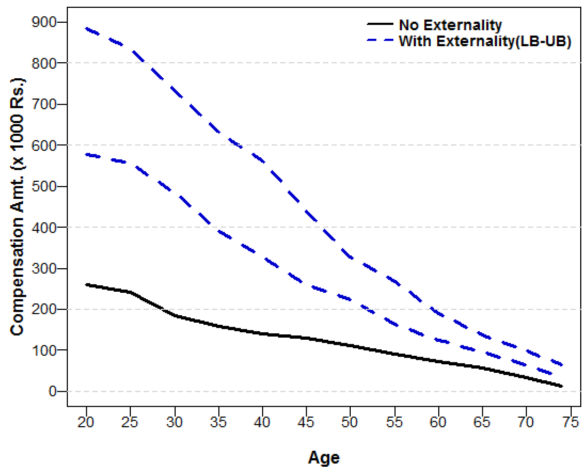


Properties of the Model. A key condition for the strategic complementarity in sanitation adoption result in appendix (D), is that the parameter ϕ which captures the effect of the externality on private consumption in the utility function is sufficiently close to zero, $\phi \approx 0$. The parameter estimates from Table (2) show ϕ to be a small positive value yet significantly different from zero.

Figure (5) overlays the simulated bounds under $\phi = 0$.[47] The simulated bounds under the model where the value of ϕ is restricted to zero, are very close to the model where ϕ is set equal to the estimated value. The simulated bounds in the figure show a monotonic shift in the bounds, under the estimated model, with a deviation in the value from $\phi = 0 \rightarrow \phi = 0.00514$. Further robustness checks are performed in Table (11) Since the bounds simulated under estimated parameter values $\widehat{\theta}$ are close to the bounds simulated under $\widetilde{\theta} : \phi = 0$ for which the theoretical result ensures existence of a highest and lowest equilibria , I use the model estimated values under $\widehat{\theta}$ to simulate policy effects. Given that the upper bound predicted under $\widehat{\theta}$ lies above the upper bound under $\phi = 0$, emphasis is placed on the lower bound of the policy effect.

[47] Table (10) also computes the simulated bounds at baseline under the assumption that parameter $\phi = 0$.

Figure 6: Household Valuation of Sanitation



Notes: This figure plots an individual household's valuation of sanitation over it's life-cycle. £1 $\approx$ $Rs.100\,(INR)$.

5.3 Household Valuation of Sanitation

The estimated model can be used to place a valuation on sanitation for a given household over its lifetime under a simulated equilibrium path. This section describes the method used to convert the value of the having sanitation into a monetary valuation by the household (in 2009 INR). To do this, I compute the expected lifetime utility of being in state x_{it} at each point in the state space after having adopted sanitation at the first period. Similarly, it is possible to compute the expected lifetime utility at each point in the state space under the scenario where household does not adopt sanitation. In order to obtain the compensating variation, I add income under the non-adoption scenario as a transfer into available cash-in-hand at each possible state and then recompute the value. This procedure is repeated until the household's expected lifetime utility with the additional income transfer is equal to its expected lifetime utility under sanitation adoption but without the hypothetical income transfer. With externality effects I compute the present value of utility from sanitation under each simulated equilibrium adoption path $\left(\overrightarrow{k}^{L}, \overrightarrow{k}^{U}\right)$. The compensating variation or the willingness-to-pay amounts can be computed at different points of the life cycle for a household given an adoption path.

Figure (6) plots the household valuation of sanitation in Indian Rs. (INR) as a function of age of the household head. Figure (6) shows that younger household heads place a higher valuation of sanitation since the gains from early adoption persist over time. Similarly older household heads value sanitation less since the time horizon to enjoy the benefits from having sanitation is shorter. The figure also plots a valuation driven by the underlying spillover effects. The solid black line plots the household valuation of sanitation without the endogenous effects driven by the underlying externality. While the dashed plots the household valuation with the endogenous effects incorporated at the upper and lower bound adoption paths respectively. On average household valuation for sanitation ranges between $Rs. 2,75,250$ (lower) and $Rs. 4,30,500$ (upper) which denotes a non-trivial amount when compared with the average household lifetime income value of $Rs. 23,76,000$.[48] The upper and lower bound for the valuation with spillover effects lie above the valuation of sanitation made by a household acting in isolation. On average the difference in valuation is 52% (lower bound) and 71% (upper bound) higher once externality effects are accounted for.

6 Counterfactual Policy Experiments

In this section, I examine the impact of different policy interventions on equilibrium sanitation coverage and welfare. In the first exercise, the question of under-adoption of sanitation is addressed by computing the socially optimal level of sanitation and comparing it with observed levels in the data. The second application focuses on the cost effectiveness of two specific policy interventions: sanitation loans and price subsidies. If a policy maker's objective is to maximize sanitation coverage? I examine which of the two policies are more cost effective. The simulations show how policy implications differ once externality effects are taken into account. In order to quantify the effect of the externality, the impact of a policy is decomposed into the private incentives (direct) from adoption and it's impact through the spillover effects (indirect). To contrast the policy implications based on maximizing coverage, I compute changes in bounds of welfare based on maximizing total welfare instead of coverage. Lastly, I study the dynamics of the age effects with potential implications for policy targeting. The impact of a policy is measured by reporting changes in the bounds of equilibrium adoption levels along with the household's willingness-to-pay for the policy under counterfactual scenarios.

6.1 Under-adoption of Sanitation

To determine if empirical sanitation coverage levels imply under-adoption, I compute the socially optimal level of sanitation adoption by solving the social planner problem for each village. I consider the problem of a constrained social planner whose objective is to allocate sanitation along to households so as to maximize utility subject to the total fixed endowment of resources. To compute the welfare under the social planner's regime, the following procedure is implemented: the total endowment is computed by aggregating the total consumption and sanitation value within a village. The marginal rate of technical substitution between consumption and sanitation is given by the market cost of sanitation by village ($price_g$). The planner induces households to solve the optimal adoption problem by re-allocating the total endowment between food consumption and sanitation, so as to maximize utility. I assume the

[48] Lifetime income value approximated using survey data from the Gwalior Nagar Nigam Seva information drive 2010-11.

Table 3: Estimated Welfare Change: Social Planner's Solution

	Total Welfare (x1000. Rs)	Sanitation Coverage
Baseline S1	9,247.2	37.0%
Social Planner	36,569.6	80.7%
Change	+295.5%	+43.7%

Notes: This table shows the change in the welfare for a representative village from enacting the social planner's solution where the total endowment is calculated with respect to the first sample period. The social planner induces households to solve the optimal adoption problem by re-allocating the total endowment between food consumption and sanitation, so as to maximize utility. A utilitarian Social Welfare Function (SWF) is maximized with equal pareto weights for each household within the village. £1 $\approx$ $Rs.\,100\,(INR)$.

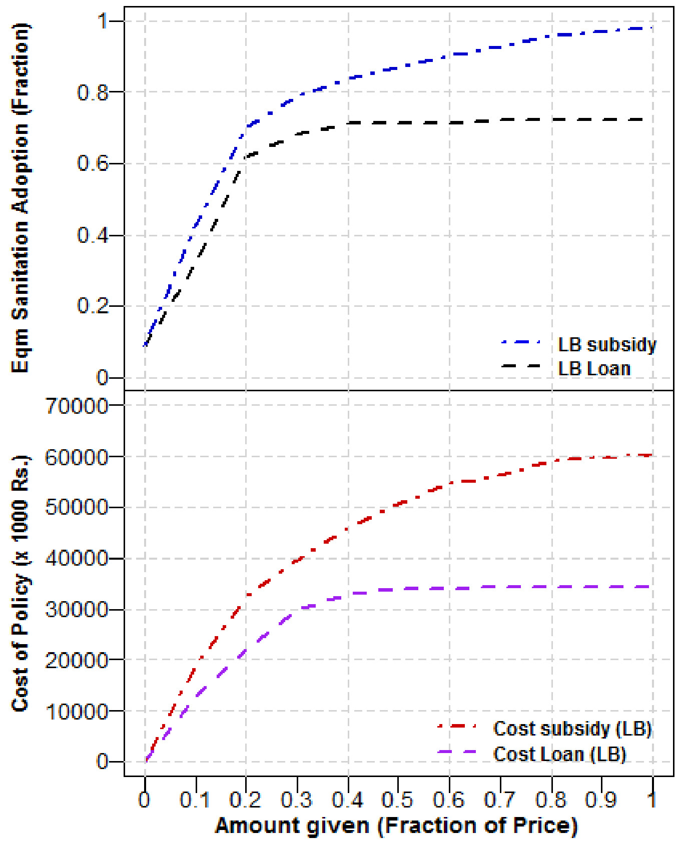
planner maximizes a utilitarian Social Welfare Function (SWF) with equal pareto weights assigned to each household within the village.[49] By changing the allocation of sanitation, moving resources between sanitation and consumption, the algorithm searches for the policy functions that maximize total household welfare until there is no other higher value attainable.

Results for a representative village are shown in Table (3). The total surplus attained is equal to $Rs.\,36$ million with 81% sanitation coverage. Compared with the baseline this reflects a 295.5% increase in household welfare and a 43.7% increase in sanitation coverage. This exercise reveals that the existing sanitation levels observed in villages are inefficient in the sense that households under-adopt sanitation and instead allocate a larger share of resources to private food consumption. This systematic under-adoption is driven by the under valuation of sanitation made by each household that fails to internalize the total benefit generated from sanitation. The difference in welfare attained between the baseline and social planner's regime reflects the cost of the externality induced by the divergence in the private and social valuation of sanitation.

Table (12) computes the utilitarian planner problem for each of the villages based on adoption level and endowment values in the first sample period. Based on the sanitation coverage observed in the data and determined under the social planner solution, the extent to which sanitation is under-adopted is computed for each of the villages. On average, the privately chosen adoption levels in the data are 53% below the socially optimal based on a utilitarian Social Welfare Function (SWF). In the subsequent counterfactual exercises, the equilibrium levels achieved under different policies are compared with the socially optimal adoption levels under the planner's problem.

[49]The socially optimal level of sanitation depends on the choice of pareto weights used in the Social Welfare Function (SWF).

Figure 7: Equilibrium Adoption: Cost of Policy & Size of Policy (lower bound)



Notes: The simulations plot the lower bounds for the predicted equilibrium sanitation level one period ahead for a gird of potential policy structures and the corresponding cost of providing said policy. Policy simulations are performed on a counterfactual village where the initial distribution of all state variables: age, assets, income and cost of sanitation $Rs. 8,628$ are held constant and the initial sanitation coverage is fixed at 0%. £1 $\approx$ $Rs. 100\,(INR)$.

6.2 Cost Effective Policy: Sanitation Loans and Price Subsidies

The social planner solution finds the observed sanitation levels to be below the socially optimal and highlights the potential role of policy interventions to increase sanitation coverage so as to increase total welfare. With a policy maker potentially constrained by the total funds available for allocation it is important to understand if the implemented policy is cost effective. The aim of this exercise is to understand whether specific policies are more cost effective than others at maximizing sanitation coverage. Specifically, I compare the simulated equilibrium coverage levels attained under sanitation loans and price subsidy policies of different sizes for a fixed cost of the policy. The objective under each policy is to correct the suboptimal allocation of sanitation by targeting the underlying market failures faced by individual households. This analysis also relates to the current debate among policy makers in the field on the appropriate choice of policy to tackle the under-adoption.

To evaluate cost effectiveness I benchmark each loan and subsidy policy against the total cost of the policy to the government to allocate the respective policy. Both loans and price subsidy policies can be allocated as a fraction $(0,1]$ of the cost of sanitation ($price_g$), where 1 denotes a 100% price subsidization or loan allocation. This determines a grid of potential policy structures for which a series of policy cost schedules and corresponding equilibrium adoption levels can be generated for each village.

Figure (7) plots the policy cost schedules and sanitation coverage curves for both price subsidies and loans across a grid of counterfactual monetary structures for a representative village. As a conservative estimate of the policy impact the figure plots only the lower bound response. The lower panel displays the relationship between a gird of loans and subsidy policy structures and the corresponding total cost of policy to the government body. The upper panel determines the sanitation coverage levels attained over the same grid of policy structures. To calculate the present cost of a loan I take an estimate of the rate of loan repayment in the local region of $\approx$ 60% to simulate loan repayment by the village population in my model.

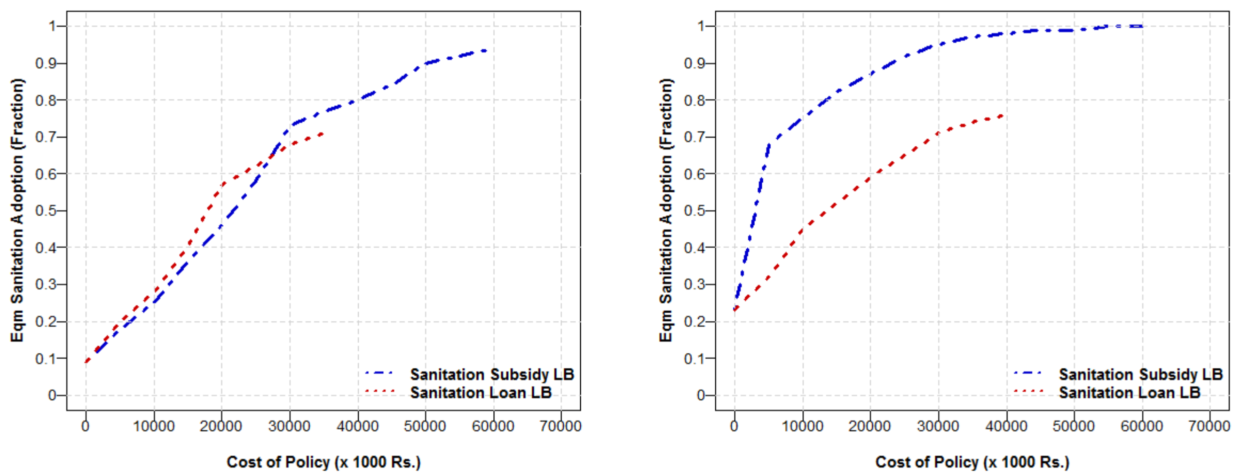
This allows me to interpolate the relationship between the total cost of the policy and the sanitation coverage level attained for that cost of intervention in Figure (8). The figure plots the lower bound response. Figure (8.a) plots the response for a village that is initially at 0% coverage level and in the next period moves to a coverage level of 9%. I find that in villages with close to zero coverage sanitation loans are as effective, if not marginally more, at achieving maximum coverage for a fixed cost of the policy. As the cost of the policy increases the the effectiveness of the loan declines. The curve for the loan stops past a certain total cost value beyond which households do not find it optimal to adopt sanitation with the take-up of a loan, at which point there is no incentive to provide a loan policy.

Figure (8.b) plots the same relationship except that the initial sanitation level is set higher at 22%. The equilibrium cost curves show a very different pattern to panel (8.a) where the subsidy policy is found to be more cost effective for all policy cost values. There is also a sharp jump in the response from 0.22 to 0.69 for the price subsidy evaluated at a policy cost value of $Rs.\,5000\,(\times 1000\,Rs)$. This is driven by the social multiplier generated by the underlying externality effect. With a low initial level of sanitation prevalence a relatively small subsidy amount induces a lot more households to adopt sanitation this effect then multiplies generating further adoption. In contrast the sanitation loan policy generates a much more modest increase in the adoption levels from 0.22 to 0.31 for the same cost of policy. Using the graph in Figure (7) to extrapolate, a $Rs.\,5000\,(\times 1000\,Rs)$ total cost of policy is associated with providing a price subsidy of 8% subsidization of the cost, to all households within the village. This exercise demonstrates heterogeneity in the impact of the policy with the initial sanitation coverage levels.

Figure 8: Equilibrium Adoption: Cost and Allocation of Policy (lower bound)

(a) Low Initial Coverage

(b) Mid-Low Initial Coverage



Notes: The simulations plot the lower bounds for the predicted equilibrium sanitation level attained under sanitation loans and price subsidies one period ahead. Policy simulations are performed on a counterfactual village where the initial distribution of all state variables: age, assets, income and cost of sanitation $Rs.8628$ are held constant and the initial sanitation coverage is fixed at 0%. £1 $\approx$ $Rs.100\,(INR)$.

6.3 Subsidies: Direct and Indirect Effects

The policy exercise in the previous section reveals sanitation price subsidies to be in general more cost effective in villages with some existing sanitation coverage. To quantify the importance of externality effects in the demand response for a household, I compare the full equilibrium impact a price subsidy with the impact generated treating the household response in isolation.

Figure (9) simulates the equilibrium bounds under different price subsidy amounts as a fraction of the cost for each of the village observed in the data.[50] The impact of the subsides is highly non linear with the initial sanitation coverage and the shape of the response curve changes as a function of the amount of the subsidy given out. Comparing the equilibrium adoption levels under lower bounds with the socially optimal adoption level in Table (12), a uniform price subsidy achieves on average 62% (under 5% subsidy), 77% (under 15% subsidy) and 92% (under 25% subsidy) of a social planner's welfare outcome and sanitation allocation.[51]

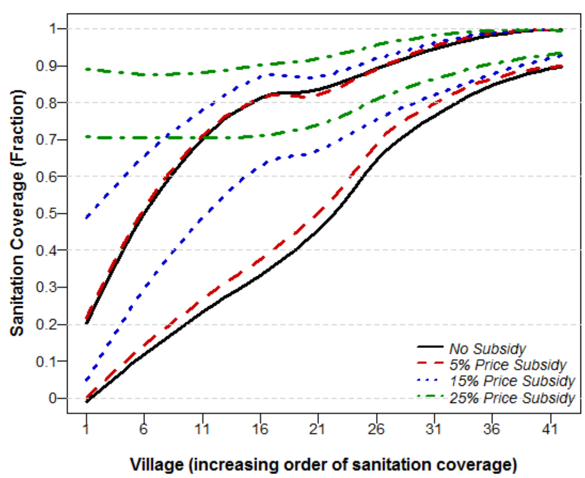
With positive externalities, the sanitation coverage levels are inefficient where each household does not fully internalize the total benefit derived from adoption. To understand the welfare gain derived for the village economy from a small shift towards the socially optimal level I compute the net welfare gain (loss) generated for a single household that is on the margin of adopting

[50]See ref Table (13)

[51]Since the true impact of the policy lies between the upper and lower bound, I compare with the lower bound of the policy as a conservative estimate.

and receives a price subsidy on the full cost of sanitation.[52] I find that provision a subsidy to a single household also produces a marginal increase in the welfare for the entire village community. The present cost of the subsidy is at $Rs. 8,628$ but the policy shifts the bounds on welfare for the recipient household by $Rs. 10,008$ (lower bound) and $Rs. 12,511$ (upper bound) from the combination of direct value of having sanitation as well as the increased utility derived from the spillover effects generated. This results in a increase in the bounds on net welfare by $Rs. 1,380$ (lower equilibrium) and $Rs. 3,883$ (upper equilibrium) of which 33% (lower bound) to 72% (upper bound) are attributed to the indirect effect. In addition to the gain for the recipient household the subsidy also generated a subsequent gain for other households in the village which amounted to $Rs. 3,181$ (lower) and $Rs. 6,253$ (upper) on aggregate or an equivalent of $Rs. 19.1$ (lower) and $Rs. 37.2$ (upper) gain per non recipient household. It is important to note that without the presence of externalities, a price distorting subsidy policy would not improve net household welfare relative to an unconditional subsidy policy.

Figure 9: Model simulation: Price Subsidy



Overall, the impact of the price subsidies on sanitation adoption is consistent with the evidence from Guiteras, Levinsohn & Mobarak (2015) under experimental policy intervention. The subsidy not only induces a greater demand response from targeted households (relative to a pure information provision intervention), but also has a non trivial impact on the adoption decision of non-targeted households within the village. This reinforces the opinion that the design of subsidy policies, for goods with spillover effects, should not be based on targeting individuals but instead be based on targeting groups of households.

[52]The welfare calculations are for a household on the margin of adopting in a representative village.

Table 4: Estimated Welfare Change: Policy Interventions

	Total Welfare (1000. Rs)	Total cost to Govt. (1000. Rs)	Net Gain (1000. Rs)	Sanitation Coverage
Baseline S1	9,247.2	-	-	37%
Social Planner	36,569.6	-	-	81%
Sanitation Loan (uniform)	21,844.1	10,726.8	11,117.3	52%
Price Subsidy (uniform)	32,321.6	18,651.2	13,670.4	73%
Price Subsidy+Uncond loan (poorest 10%)	33,728.4	18,651.2	15,077.2	68%

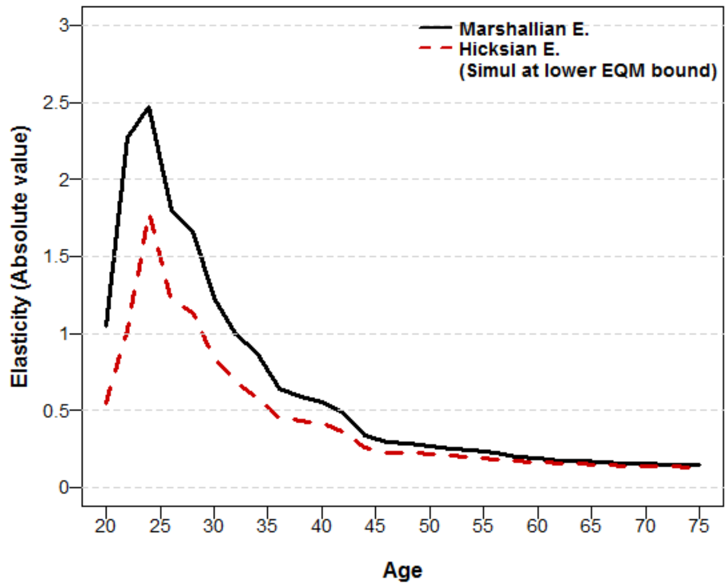
Notes: This table shows the change in the welfare for a representative village from enacting the social planner's solution and under three different policy interventions: Sanitation Loan (uniform), Price subsidy (uniform) and a combination of price subsidy + Unconditional Loan (poorest 10%). A utilitarian Social Welfare Function (SWF) is maximized with equal pareto weights for each household within the village. £1 $\approx$ $Rs.100\,(INR)$.

6.4 Dynamics over age

A price subsidy generates a substitution effect as well as an income effect on the demand response of a recipient household. Figure (10) decomposes the impact of a subsidy into its income and substitution effect components. The figure plots the absolute value of the Marshallian (uncompensated) and Hicksian (compensated) price elasticities at a lower equilibrium bound for a representative household over its life-cycle. The Hicksian elasticity measures the pure price effect of the good keeping the utility level fixed. While the vertical difference between the two curves is the residual income effect generated from the increase in the effective budget that a household has available to spend.

Both the Marshallian and Hicksian elasticity (in absolute value) decrease over the life-cycle as marginal utility from adoption decreases with age, this feature is driven by the life-cycle structure subject to terminal value assumptions. The income effect which also diminishes with age is relatively larger at younger ages. The excess sensitivity of the demand response earlier in the life-cycle maybe driven by binding liquidity constraints faced by younger households. This is particularly relevant at younger ages where a larger fraction of the total demand response is attributed to the income effect relative to older ages. Unable to borrow against their future income, younger households who have yet to accumulate sufficient assets respond more on the income effect margin than the price effect, upon receiving the price subsidy. Figure (6) also shows that a household's valuation of sanitation decreases with age. With a loan policy a household is able to move resources across time and borrow against future realizations of income to bring forward sanitation adoption. A household's decision to take a sanitation loan compares the value generated from the sanitation between today and tomorrow. Since a household's private valuation from sanitation declines with age, loans would be a preferred policy for targeting younger cohorts who place a higher valuation on sanitation adoption.

Figure 10: Price Elasticity: Substitution & Income Effects



Notes: The figure plots the Marshallian and Hicksian demand elasticity (in absolute value) for a household head over its life-cycle. The household response is simulated at a lower equilibrium bound.

7 Conclusion

To understand the effectiveness of interventions that aim to maximize sanitation coverage, requires the capability of predicting and comparing outcomes under alternative counterfactual policies. This paper examines the impact of two specific policy interventions: loans v. price subsidies, on sanitation adoption behaviour in a context where household decisions interrelate due to externality effects. I formulate and estimate a dynamic household demand for sanitation that incorporates interdependence of sanitation adoption choice. To identify the model's parameters, I use a combination of household panel dataset along with exclusion restrictions that provide identifying variation at the household and village level. The model is used to compute equilibrium adoption levels and simulate the effect of loans and subsidy policies for sanitation where the recipient household's adoption decision imposes externalities on others.

I illustrate how the framework can be informative about the effectiveness and efficiency of different policies, where otherwise distorting policies instead lead to higher welfare gains when the household decision is no longer treated in isolation. A sanitation adoption subsidy to a single household costing $Rs. 8,628$ improved net welfare in a low case by $Rs. 1,380$ and a high case by $Rs. 3,883$. A large fraction of the impact, between 33% (lower bound) to 72% (upper bound), accrues to non-recipient households. These spillover effects suggest that adoption subsidies for sanitation should not be thought of as targeting individual households, but instead as targeting the whole village or groups of households.

While a significant proportion of sanitation prevalence is driven by price incentives, a small number of households do face binding liquidity constraints for whom targeted loans is a cost effective policy. The ultimate choice of policy is strongly driven by the trade-off between the total cost considerations and the targeting objectives as well as level of sanitation coverage in the targeted village. If the objective of the policy is to 'reach' the maximum number of households, in most cases it is cost effective to provide price subsidies to incentivize adoption of sanitation. In contrast, sanitation loans are found to be cost effective in villages with close to zero initial coverage.

One of the main predictions of the model is that subsidizing the cost of sanitation is a cost effective policy with the presence of externalities. An important extension of this paper would be to combine the structural analysis with field experiment results to disentangle and identify the exact mechanisms that generates this externality. There are still open questions on the precise mechanism that drives the interdependence of sanitation adoption. Other than a health externality other suggested mechanisms include, the presence of information externalities as well as infrastructure and amenity spillovers generated from collective adoption. A better understanding of the mechanisms will not only improve our understanding of the nature of the gains derived from adoption but could also provide insights on improving the efficiency of future policy interventions.

Although the empirical application focuses on the specific topic of sanitation, the structure developed in this paper can be used to study other applications where household/individual decisions interrelate due to spillover effects. The findings in this paper highlight the fact that, when externalities exist, accounting for equilibrium interactions and quantifying its effect has important policy implications. The structure can also be extended to study adoption patterns of other preventive healthcare goods in the developing world for e.g. vaccinations. The size and nature of the externality depends on the specific characteristics of different healthcare goods. The degree of 'social benefit' associated with vaccination adoption may differ from sanitation and thus would provide different policy implications. The analysis in this paper finds subsidies to be a more 'favoured' policy the larger is the impact of the externality or the degree of 'social benefit' associated with the healthcare good. These extensions can provide useful information that can help poor communities as a whole to minimize inefficiencies and absorb the overall benefits thus tackling poverty and mitigating its detrimental effects.

8 References

Abbring, J.H. (2010): "Identification of Dynamic Discrete Choice Models," *Annual Review of Economics*, 2, 367-394.

Adukia, A. (2016): "Sanitation and Education," *American Economic Journal: Applied Economics*, forthcoming.

Aguirregabiria, V. and P. Mira (2002): "Swapping the Nested Fixed Point Algorithm: A Class of Estimators for Discrete Markov Decision Models," *Econometrica*, 70(4), 1519-1543.

Aguirregabiria, V. and P. Mira (2007): "Sequential Estimation of Dynamic Discrete Games," *Econometrica*, 75(1), 1-53.

Alessie, R., M. Devereux and G. Weber (1997): "Intertemporal Consumption, Durables and Liquidity Constraints: A Cohort Analysis," *European Economic Review*, 41(1), 37-59.

Altug, S. and R. Miller (1998): "The effect of work experience on femaly wages and labour supply," *Review of Economic Studies*, 65(1), 45-85.

Arcidiacono, P., P. Bayer, J.R. Blevins and P. Ellickson (2016): "Estimation of Dynamic Discrete Choice Models in Continuous Time with an Application to Retail Competition," *Reveiw of Economic Studies*, 83(3), 889-931.

Arcidiacono, P. and R. Miller (2011): "Conditional Choice Probability Estimation of Dynamic Discrete Choice Models with Unobserved Heterogeneity," *Econometrica*, 79(6), 1823-1867.

Attanasio, O., J. Banks, C. Meghir and G. Weber (1999): "Humps and Bumps in Lifetime Consumption," *Journal of Business & Economic Statistics*, 17(1), 22-35.

Attanasio, O. and M. Browning (1995): "Consumption over the Life Cycle and over the Business Cycle," *American Economic Review*, 85(5), 1118-1137.

Attanasio, O. and G. Weber (1995): "Is Consumption Growth Consistent with Intertemporal Optimization? Evidence for the Consumer Expenditure Survery," *Journal of Political Economy*, 103(6), 1121-1157.

Attanasio, O. and G. Weber (2010): "Consumption and Saving: Models of Intertemporal Allocation and Their Implications for Public Policy," *Journal of Economic Literature*, 48, 693-751.

Augsburg, B. and P. Rodriguez (2015): "Sanitation and child health in India," *IFS Working Papers (W15/32)*

Bajari, P., L. Benkard and J. Levin (2007): "Estimating dynamic models of imperfect competiton," *Econometrica*, 75(5), 1331-1370.

Bajari, P., H. Hong and S.P. Ryan (2010): "Identification and Estimation of a Discrete Game of Complete Information," *Econometrica*, 78(5), 1529-1568.

Bajari, P., H. Hong, J. Krainer and D. Nekipelov (2010): "Estimating Static Models of Strategic Interactions," *Journal of Business & Economic Statistics*, 28(4), 469-482.

Bajari, P., H. Hong and D. Nekipelov (2013): "Game Theory and Econometrics: A Survey of Some Recent Research," *Advances in Economics and Econometrics, Tenth World Congress*, Ed: D. Acemoglu, M. Arellano & E. Dekel, Vol 3(1), 3-52.

Bennett, D. (2012): "Does Clean Water Make You Dirty? Water Suppy and Sanitation in the Philippines," *Journal of Human Resources*, 47(1), 146-173.

Bill & Melinda Gates Foundation (2011): "Gates Foundation Launches Effort to Reinvent the Toilet," *https://docs.gatesfoundation.org/Documents/wsh-reinvent-the-toilet-challenge.pdf*

Björkegren, D. (2014): "The Adoption of Network Goods: Evidence from the Spread of Mobile Phones in Rwanda," *working paper*, Brown University.

Blevins, J.R. (2014): "Nonparametric identification of dynamic decision processes with discrete and continuous choices," *Quantitative Economics*, 5, 531-554.

Brock, W.A. and S. Durlauf (2001): "Discrete Choice with Social Interactions," *Review of Economic Studies*, 68(2), 235-260.

Brock, W.A. and S. Durlauf (2007): "Identification of Binary Choice Models with Social Interactions," *Journal of Econometrics*, 140(1), 52-75.

Cameron, L., M. Shah and S. Olivia (2013): "Impact Evaluation of a Large-Scale Rural Sanitation Project in Indonesia," Policy Research Working Paper 6360, *The World Bank, Water & Sanitation Program*.

Chesher, A. (1991): "The effect of measurement error," *Biometrika*, 78(3), 451-462.

Coffey, D. (2014): "Sanitation Externalities, disease, and children's anemia," *Working Paper*, Princeton University.

De Paula, A. (2009): "Inference in a synchronization game with social interactions," *Journal of Econometrics*, 148(1), 56-71.

De Paula, A. and X. Tang (2012): "Inference of signs of interaction effects in simultaneous games with incomplete information," *Econometrica*, 80(1) 143-172.

Doraszelski, U. and J.F. Escobar (2010): "A theory of regular Markov perfect equilibria in dynamic stochastic games: Genericity, stability and purification," *Theoretical Economics*, 5(3), 369-402.

Doraszelski, U. and M. Satterthwaite (2010): "Computable Markov-perfect industry dynamics," *RAND Journal of Economics*, 41(2), 215-243.

Duflo, E., M. Greenstone, R. Guiteras and T. Clasen (2015): "Toilets Can Work: Short and Medium Run Health Impacts of Addressing Complementarities and Externalities in Water and Sanitation," *NBER Working Paper No. 21521*

French, E. (2005): "The Effects of Health, Wealth, and Wages on Labour Supply and Retirement Behaviour," *Review of Economic Studies*, 72(2), 395-427.

French, E. and J.B. Jones (2011): "The Effect of Health Insurance and Self-Insurance on Retirement Behaviour," *Econometrica*, 79(3), 693-732.

Fu, C. and J. Gregory (2016): " Estimation of an Equilibrium Model with Externalities: Combining the Strengths of Structural Models and Quasi-Experiments," *Working Paper*, University of Wisconsin.

Gautam, S. (2015): "Quantifying welfare effect in the presence of externalities: An ex-ante evaluation of a sanitation intervention," *Working Paper*, University College London.

Geruso, M. and D. Spears (2015): "Neighbourhood Sanitation and Infant Mortality," *American Economic Journal: Applied Economics*, R&R

Gourinchas, P.O. and J. Parker (2002): "Consumption over the life cycle," *Econometrica*, 70(1), 47-89.

Guiteras, R., J. Levinsohn and A.M. Mobarak (2015): "Encouraging Sanitation Investment in the Developing World: A Cluster-Randomized Controlled Trial," *Science*, Vol. 348(6237), 903-906.

Hammer, J. and D. Spears (2013): "Village sanitation externalities and children's human capital: Evidence from a randomized control experiment by the Maharashtra government," *Research Program in Development Studies, Working Paper*, Princeton University.

Honore, B.E. and L. Hu (2015): "Poor (Wo)man's Bootstrap," *FRB of Chicago Working Paper No. 2015-01.*

Hotz, V.J. and Miller, R. (1993): "Conditional Choice Probabilities and the Estimation of Dynamic Models," *Review of Economic Studies*, 60(3), 497-529.

Hotz, V.J., R. Miller, S. Sanders and J. Smith (1994): "A Simulation Estimator for Dynamic Models of Discrete Choice," *Review of Economic Studies*, 61(2), 265-289.

Iskhakov, F., J. Rust and B. Schjerning (2016): "Recursive Lexiographical Search: Finding all Markov Perfect Equilibria of Finite State Directional Dynamic Games," *Review of Economic Studies*, 1-46.

Jia, P. (2008): "What Happens When Wal-Mart Comes to Town: An Empirical Analysis of the Discount Retailing Industry," *Econometrica*, 76(6), 1263-1316.

Lazzati, N. (2015): "Treatment response with social interactions: Partial identification via monotone comparative statics," *Quantitative Economics*, 6, 49-83.

Lee, D. and K. Wolpin (2009): "Intersectoral Labour Mobility and the Growth of the Service Sector," *Econometrica*, 74, 1-46.

Lee, R.S. and A. Pakes (2009): "Multiple Equilibria and Selection by Learning in an Applied Setting," *Economic Letters*, 104(1), 13-16.

Magnac, T. and D. Themar (2002): "Identifying Dynamic Discrete Decision Processes," *Econometrica*, 70, 801-816.

Manski, C. (2013): "Identification of treatment response with social interactions," *Econometrics Journal*, 16, S1-S23.

Manski, C. (1993): "Identification of Endogenous Social Effects: The Reflection Problem," *Reveiw of Economic Studies*, 60(3), 531-542.

Mara D., J. Lane, B. Scott and D. Trouba (2010): " Sanitation and Health," *PLoS Medicine*, 7(11): e1000363.

Maskin, E. and J. Tirole (2001): "Markov Perfect Equilibrium, I: Observable Actions," *Journal of Economic Theory*, 100(2), 191-219.

Miguel, E. and M. Kremer (2004): "Worms: Identifying Impacts of Education and Health in the Presence of Treatment Externalities," *Econometrica*, 72(1), 159-217.

Milgrom, P. and C. Shannon (1994): "Monotone Comparative Statics," *Econometrica*, 62(1), 157-180.

Pakes, A., M. Ostrovsky and S. Berry (2007): "Simple Estimators for the Parameters of Discrete Dynamic Games (with Entry/Exit Examples)," *Rand Journal of Economics*, 38(2), 373-399.

Palumbo, M.G. (1999): "Uncertain Expenses and Precautionary Saving Near the End of the Life Cycle," *Review of Economic Studies*, 66(2), 395-421.

Pesendorfer, M. and P. Schmidt-Dengler (2010): "Sequential Estimation of Dynamic Discrete Games: A Comment," *Econometrica*, 78(2), 833-842.

Pesendorfer, M. and P. Schmidt-Dengler (2008): "Asymptotic Least Squares Estimators for Dynamic Games," *Review of Economic Studies*, 75(3), 901-928.

Pesendorfer, M. and P. Schmidt-Dengler (2003): "Identification and Estimation of Dynamic Games," *NBER Working Paper Series*,Working Paper 9726

Reguant, M. (2016): "Bounding Outcomes in Counterfactual Analysis," Working Paper, Northwestern University

Rust, J. (1994): "Structural Estimation of Markov Decision Processes," in *Handbook of Econometrics*, 4, ed. R. Engle & D. McFadden. Amsterdam: North Holland, 3081-3143.

Rust, J. (1987): "Optimal replacement of GMC bus engines: an empirical model of Harold Zurcher," *Econometrica*, 55(5), 999-1033.

Spears, D. (2012): "Effects of Rural Sanitation on Infant Mortality and Human Capital: Evidence from India's Total Sanitation Campaign," *Working Paper 2012*, Princeton University.

Spears, D. (2013): "The nutritional value of toilets: How much international variation in child height can sanitation explain?" *World Bank Policy Research Working Paper 6351*.

Spears, D. and S. Lamba (2013): "Effects of Early-Life Exposure to Sanitation on Childhood Cognitive Skills," *Working Paper 6659*, World Bank Sustainable Development Network Water and Sanitation Program Unit.

Stopnitzky, Y. (2014): "Throwing Money Down the Toilet? The Impact of Government Subsidies on Latrine Adoption in India," *Working paper*, University of San Francisco.

Stokey, N and R. Lucas, with E. Prescott (1989): *Recursive Methods in Economic Dynamics.* Cambridge, Mass: Harvard University Press, 1989.

Tarski, A. (1955): "A Lattice-Theoretical Fixpoint and Its Applications," *Pacific Journal of Mathematics*, 5(), 285-309.

Topkis, D. (1978): "Minimizing a Submodular Function of a Lattice," *Operations Research*, 26(2), 305-321.

Topkis, D. (1998): "Supermodularity and Complementarity," Princeton, NJ: Princeton University

Zeldes, S.P. (1989): "Consumption and Liquidity Constraints: An Empirical Analysis," *Journal of Political Economy*, 97(2), 305-346.

APPENDIX

A Data

A.1 Estimation of age profiles

I control for cohort effects to obtain the life-cycle profiles using data from different household cohorts. The age profiles of interest such as, sanitation adoption and asset accumulation by age of household head depicts dynamics that the model should be able to replicate. The main concern, when constructing age profiles that account for cohort effects, is with effect of family size, year effects and household specific effects. To account for cohort effects, which is just the average fixed-effect of all households in a single cohort, I follow the approach discussed in French (2005) to obtain age profiles for both sanitation adoption and asset accumulation over a household head's lifetime.

B Identification

The identification approach is based on the insight from Hotz & Miller (1993) and Hotz, Miller, Sanders & Smith (1994) where Bellman equations can be interpreted as 'moment conditions' and can be used to recover structural parameters (Magnac & Thesmar 2002). Additional assumptions with regards to the continuous choice follow from Bajari, Benkard & Levin (2007) and Blevins (2014).

$$\left[v_i\left(d_i=1,c_i^o,x\right)-v_i\left(d_i=0,c_i^o,x\right)-\mu_g\right]=\ln\underbrace{\left[p_i\left(d_i=1|x\right)\right]}_{obsv}-\ln\underbrace{\left[1-p_i\left(d_i=1|x\right)\right]}_{obsv} \tag{B.1}$$

Equation (B.1) shows that the difference in the choice specific value functions for any state x can be recovered from knowledge of the observed conditional choice probabilities denoted by:[53]

$$\text{for all } i \text{ \& all } x, \quad p_i\left(d_i=1|x\right)=\frac{\exp\left(v_i\left(d_i=1,c_i^o,x;\sigma\right)-v_i\left(d_i=0,c_i^o,x;\sigma\right)\right)}{1+\exp\left(v_i\left(d_i=1,c_i^o,x;\sigma\right)-v_i\left(d_i=0,c_i^o,x;\sigma\right)\right)} \tag{B.2}$$

The choice-specific value function can be written as:

$$v_i\left(d_i,c_i^o,x;\sigma\right)\equiv\max_{c\in\mathcal{C}}\left\{u_i\left(d_i,c_i,x,\xi;\sigma\right)+\beta\mathbb{E}\left[V_i\left(x';\sigma\right)|x,d_i,c_i\right]\right\}$$

[53]For ease of exposition time subscript is subsumed.

If $d_i = 0$, this relationship identifies $v_i(d_i = 0, c_i, x; \sigma)$ under the normalization assumption $u_i(d_i = 0, c_i, x; \sigma) = 0$:

$$v_i(d_i = 0, c_i, x; \sigma) \equiv 0 + \underbrace{\beta \mathbb{E}\left[\ln\left(\sum_{k=0}^{K} \exp\left[v_i\left(d_i = k, c_i, x^{'}; \sigma\right) - v_i\left(d_i = 0, c_i, x^{'}; \sigma\right)\right]\right) | x, d_i = 0, c_i\right]}_{A \Rightarrow identifiable \,\&\, estimable}$$

$$+ \underbrace{\beta \mathbb{E}\left[v_i\left(d_i = 0, c_i, x^{'}; \sigma\right) | x, d_i = 0, c_i\right]}_{B} + \beta \widehat{\gamma}$$

Term A on the R.H.S is identifiable and estimable from the data by inverting the choice probabilities. Under finite horizon, term B can be backed out via backward recursion, given assumptions on terminal value function, thus recovering the baseline choice-specific value function $v_i(d_i = 0, c_i, x; \sigma)$. Subsequently, $v_i\left(d_i = 1, c_i^o, x; \sigma\right)$ can be identified by inverting the choice probabilities by taking logs on both sides of the Equation (B.2).

C Estimation

Conditional Choice Probability (*CCP*). The conditional choice probabilities are estimated from the observed data. The underlying assumption to obtain consistent equilibrium choice probability estimates relies on the data being generated from the same Markov profile. This assumption however may not hold true when data is pooled across multiple villages. The overall sample of 42 villages are divided into four groups based on village level observables and geographic proximity to one another.

Partially observed sample. To account for the fact that only part of the entire village household behaviour is observed. I implement the correction method from Chesher (1991) extended in Gautam (2015) to account for this source of measurement error in the data and its impact on the choice probability estimates.

Income Process. The function relating age and education to income earnings is given by:

$$\ln y_{it} = f(age_{it}, edu_i) + z_{it} + \xi_{it}$$

$$f(age_{it}, edu_i) = \psi_0^y + m_a^y(age_{it}) + \psi_{edu1}^y edu_i(yrs) + \psi_{edu2}^y (edu_i(yrs))^2 + \psi_3^y [age_{it} \times edu_i(yrs)]$$

$$z_{it} = \rho z_{it-1} + u_{it}, \quad u_t \sim N\left(0, \sigma_u^2\right)$$

where $m_a^y(age_{it})$ are piecewise linear functions in age of the household head with nodes at 20, 25 and 50. The education of the primary earner (household head) is measured in years $edu_i(yrs)$

along with an interaction term between age and education. The permanent income also includes an A.R.(1) component with persistence parameter calibrated at $\rho = 1$ and the variance of the permanent shocks σ_u^2. Measurement error ξ_{it} shocks are distributed *i.i.d* with mean zero and variance σ_ξ^2.

Equilibrium Condition Inequalities. To estimate $\widehat{g}_i$ I compute estimates for $\widehat{V}_i\left(x; \sigma'_{i(k)}, \widehat{\sigma}_{-i}, \theta, \psi\right)$ for a set of alternatives policies σ'_i. To implement this, let $\{\lambda_k\}_{k=1,\ldots,n_I}$ be a set of chosen inequalities from Λ indexed by $\left(i,\, x,\, \sigma'_i\right)$ which represent *i.i.d* draws from $H(\cdot)$. BBL (2007) prescribe a variety of ways to choose inequalities. The method of selecting inequalities will have implications for efficiency, but for consistency the only requirement is that $H(\cdot)$ has sufficient support to yield identification.

I draw households i (ε_i) and states x at random and then consider alternative strategies σ'_i that are slight perturbations of the estimated policy $\sigma_i\left(x, \varepsilon_i; \widehat{\psi}\right)$ i.e., $\sigma'_i\left(x, \varepsilon_i\right) = \sigma_i\left(x, \varepsilon_i; \widehat{\psi}\right) + \epsilon$. Given that the strategy σ_i is a tuple consisting of $\left[\delta'_i\left(x, \varepsilon_i\right), c_i^{o\prime}\left(x_i\right)\right]$ the perturbation is on both the discrete decision rule as well as the continuous consumption policy c_i^o for each household. For each chosen inequality, λ_k the next step is to use the forward simulation procedure from section (4.2) to construct sample analogues for each of the $V_i\left(x; \sigma'_{i(k)}, \sigma_{-i}, \theta, \psi\right)$ value functions at the perturbed policy $\sigma'_{i(k)}$ drawn. In practice, two different sizes for the inequality draws was used $n_I = 500$ and $n_I = 1000$. No discernible difference in magnitude of final estimates was found as n_I increased from 500 to 1000.

Standard Errors. The standard errors are computed using bootstrap re-sampling. The villages to which households belong are the unit of re-sampling over which repeated samples of 42 villages are drawn with replacement. Bootstrap is performed over both estimation stages. The first stage elements of the estimation are repeated over each bootstrap sample followed by the second stage. A total of 250 bootstrap samples were drawn to construct standard errors.

D Simulation

D.1 Supermodular Objective Function

The objective function of a household i at time t can be expressed as:

$$v_i\left(d_{it}, c_{it}^o, x_t; \sigma_t\right) = u_i^{\sigma_t}\left(c_{it}, d_{it}, x_{it}\right) + \beta \sum_{x_{t+1}} V_i\left(x_{t+1}; \sigma_{t+1}\right) \, f_i^{\sigma_t}\left(x_{t+1} | x_t, d_{it}, c_{it}\right)$$

Define the following notation:

$\hat{c}_{it}^1 = (1+r)A_{it} - A_{it+1} + y_{it} - price_t$

$\hat{c}_{it}^0 = (1+r)A_{it} - A_{it+1} + y_{it}$

$x_{it} = \Big(a_{it}, A_{it}, y_{it}, k_{it-1}, \bar{k}_{t-1}, price_t, \xi_{it}\Big)$

$\hat{u}_{it,c}^d = \frac{\partial}{\partial c_{it}}\left[u_i^{\sigma_t}\left(c_{it}, d_{it}, x_{it}\right)\right]$

$\hat{u}_{it,cc}^d = \frac{\partial^2}{\partial c_{it}^2}\left[u_i^{\sigma_t}\left(c_{it}, d_{it}, x_{it}\right)\right]$

$v_{it}^d = v_i\left(d_{it}, c_{it}, x_t; \sigma_t\right)$

Denote the objective functions of an individual household with states x_t, that adopts at time t (i.e $d_{it} = 1$) with $v_{it}^1 = v_i\left(d_{it} = 1, c_{it}^1, x_t; \sigma_t\right)$ and of a household that does not adopt (i.e $d_{it} = 0$) with $v_{it}^0 = v_i\left(d_{it} = 0, c_{it}^0, x_t; \sigma_t\right)$. The conditional choice-specific value functions are expressed as:

$$\begin{aligned}
v_i\left(d_{it} = 1, c_{it}^1, x_t; \sigma_t\right) &= \left(c_{it}^1\right)^{\nu}\left(1 + \eta k_{it-1} + \phi \bar{k}_{t-1}\right) + \alpha k_{it-1} + \gamma k_{it-1} \bar{k}_{t-1} \\
&\quad + \beta \textstyle\sum_{x_{t+1}} V_i\left(x_{t+1}; \sigma_{t+1}\right) \, f_i^{\sigma_t}\left(x_{t+1} | x_t, 1, \hat{c}_{it}\right) \\
v_i\left(d_{it} = 0, c_{it}^0, x_t; \sigma_t\right) &= \left(c_{it}^0\right)^{\nu}\left(1 + \eta k_{it-1} + \phi \bar{k}_{t-1}\right) + \alpha k_{it-1} + \gamma k_{it-1} \bar{k}_{t-1} \\
&\quad + \beta \textstyle\sum_{x_{t+1}} V_i\left(x_{t+1}; \sigma_{t+1}\right) \, f_i^{\sigma_t}\left(x_{t+1} | x_t, 0, \hat{c}_{it}\right)
\end{aligned}$$

Therefore, the unconditional value function is given by:

$$V_i(x_t; \sigma_t) = \int \max_{d_{it} \in \mathcal{D}_{i,t}, c_{it} \in \mathcal{C}_{i,t},} \left\{ v_i\left(d_{it}, c_{it}, x_t; \sigma_t\right) + \varepsilon_{it} \right\} g(\varepsilon_{it}) d\epsilon_{it}$$

$$V_i(x_t; \sigma_t) = p_i^{\sigma_t}(d_{it} = 1 | x_t) \cdot \left[v_i(d_{it} = 1, c_{it}^o, x_t; \sigma_t) + \varepsilon_{it}^1\right] + \left[1 - p_i^{\sigma_t}(d_{it} = 1 | x_t, \sigma_t)\right] \cdot \left[v_i(d_{it} = 0, c_{it}^o, x_t; \sigma_t) + \varepsilon_{it}^0\right]$$

The expected value of the continuation value at time $t-1$ is:

$$p^{\sigma_t}(d_{it}=1|x_t) = Pr\left(v_i\left(d_{it}=1,c_{it}^1,x_t;\sigma_t\right)+\varepsilon_{it}^1 \geq v_i\left(d_{it}=0,c_{it}^0,x_t;\sigma_t\right)+\varepsilon_{it}^0\right)$$

$$= \begin{cases} P\left(v_i(d_{it}=1,c_{it}^1,x_t;\sigma_t)-v_i(d_{it}=0,c_{it}^0,x_t;\sigma_t)\right) & k_{it-1}=0 \\ 0 & k_{it-1}=1 \end{cases}$$

where P is a twice continuously differentiable and weakly increasing function. Integrating over the space of possible states x_{t+1} one gets the expected utility:

$$E_{t-1}[V_i(x_t;\sigma_t)] = \sum_{x_t}\left\{v_i\left(d_{it}=0,c_{it}^0,x_t;\sigma_t\right)\left[1-p^{\sigma_t}(d_{it}=1|x_t)\right]+\right.$$

$$\left. + v_i(d_{it}=1,c_{it}^1,x_t;\sigma_t)\left[p^{\sigma_t}(d_{it}=1|x_t)\right]\right\} f_i^{\sigma_t}\left(x_{t+1}|x_t,d_{it},\hat{c}_{it}\right)$$

where $p^{\sigma_t}(d_{it}=1|x_t)$ is the probability that a household facing states x_t decides to adopt. The functions $v_i(d_{it}=1,c_{it}^1,x_t;\sigma_t), v_i(d_{it}=0,c_{it}^0,x_t;\sigma_t)$ - if the solution for A_{it+1} is interior - have derivatives with respect to state A_{it} equal to:

$$\frac{\partial}{\partial A_{it}}\left[v_i\left(d_{it}=1,\hat{c}_{it}^1,x_t;\sigma_t\right)\right] = \nu\left[\hat{c}_{it}^1\right]^{\nu-1}(1+r)(1+\eta k_{it-1}+\phi\bar{k}_{t-1})$$

$$\frac{\partial}{\partial A_{it}}\left[v_i\left(d_{it}=0,\hat{c}_{it}^0,x_t;\sigma_t\right)\right] = \nu\left[\hat{c}_{it}^0\right]^{\nu-1}(1+r)(1+\eta k_{it-1}+\phi\bar{k}_{t-1})$$

because of the Envelope condition. Specifically,

$$\tfrac{\partial}{\partial A_{it}}\left[v_i\left(d_{it}=0,\hat{c}_{it}^0,x_t;\sigma_t\right)\right] = \nu\left[\hat{c}_{it}^0\right]^{\nu-1}(1+r)(1+\eta k_{it-1}+\phi\bar{k}_{t-1})+$$

$$+\tfrac{dA_{it+1}^*}{dA_{it}}\left[-\nu\left[\hat{c}_{it}^0\right]^{\nu-1}(1+\eta k_{it-1}+\phi\bar{k}_{t-1})+\beta\tfrac{\partial}{\partial A_{it+1}}\sum_{x_{t+1}}V_i\left(x_{t+1};\sigma_{t+1}\right) f_i^{\sigma_t}\left(x_{t+1}|x_t,d_{it},c_{it}\right)\right]$$

Notice that the second line (in the equation above) is equal to zero if the household is in an interior solution for A_{it+1} at time t because of the FOCs with respect to A_{it+1}^*. This is also true in a corner solution, because in such a case $\frac{dA_{it+1}^*}{dA_{it}}=0$. Thus it is true for any optimal level of A_{it+1}.

$$\frac{\partial}{\partial A_{it}} \sum_{x_t} V_i(x_t;\sigma_t) f_i^{\sigma_{t-1}}(x_t|x_{t-1}, d_{it-1}, \hat{c}_{it-1}) =$$

$$\sum_{x_t} \left\{ \frac{\partial}{\partial A_{it}} \left[v_i\left(d_{it}=0, \hat{c}^0_{it}, x_t;\sigma_t\right)\right] \left[1 - p^{\sigma_t}(d_{it}=1|x_t)\right] + \frac{\partial}{\partial A_{it}} \left[v_i\left(d_{it}=1, \hat{c}^1_{it}, x_t;\sigma_t\right)\right] \left[p^{\sigma_t}(d_{it}=1|x_t)\right] \right.$$

$$\left. + \frac{\partial}{\partial A_{it}} \left[p^{\sigma_t}(d_{it}=1|x_t)\right] \left[v_i\left(d_{it}=1, \hat{c}^1_{it}, x_t;\sigma_t\right) - v_i\left(d_{it}=0, \hat{c}^0_{it}, x_t;\sigma_t\right)\right] \right\} f_i^{\sigma_{t-1}}(x_t|x_{t-1}, d_{it-1}, \hat{c}_{it-1})$$

$$= \sum_{x_t} \left\{ u_c(\hat{c}^0_{it}, x_t)[1 - p^{\sigma_t}(d_{it}=1|x_t)] + u_c(\hat{c}^1_{it}, x_t)\left[p^{\sigma_t}(d_{it}=1|x_t)\right] \right.$$

$$\left. + P'\left(v^1_{it} - v^0_{it}\right)\left[v_i(d_{it}=1, c^1_{it}, x_t;\sigma_t) - v_i(d_{it}=0, c^0_{it}, x_t;\sigma_t)\right](1 + \eta k_{it-1} + \phi \bar{k}_{t-1})\nu \left[\left(c^1_{it}\right)^{\nu-1} - \left(c^0_{it}\right)^{\nu-1}\right] \right\}$$

$$\cdot f_i^{\sigma_{t-1}}(x_t|x_{t-1}, d_{it-1}, \hat{c}_{it-1})$$

Now update time to t:

$$\frac{\partial}{\partial A_{it+1}} \sum_{x_{t+1}} V_i(x_{t+1};\sigma_{t+1}) f_i^{\sigma_t}(x_{t+1}|x_t, d_{it}, \hat{c}_{it}) =$$

$$\sum_{x_{t+1}} \left\{ \hat{u}^0_c(1+r)[1 - p^{\sigma_{t+1}}(d_{it+1}=1|x_{t+1})] + \hat{u}^1_c(1+r)\left[p^{\sigma_{t+1}}(d_{it+1}=1|x_{t+1})\right] \right.$$

$$+ P'\left(v^1_{it+1} - v^0_{it+1}\right))[v_i(d_{it+1}=1, c^1_{it+1}, x_{t+1};\sigma_{t+1}) - v_i(d_{it+1}=0, c^0_{it+1}, x_{t+1};\sigma_{t+1})]$$

$$\left. \cdot(1 + \eta k_{it} + \phi \bar{k}_t)\nu \left[\left(c^1_{it+1}\right)^{\nu-1} - \left(c^0_{it+1}\right)^{\nu-1}\right] \right\} f_i^{\sigma_t}(x_{t+1}|x_t, d_{it}, \hat{c}_{it})$$

REQUIREMENTS

D.1.1 i-Constant Differences in A_{it+1}, σ_t

Consider two strategy set σ'_t and σ_t such that $\sigma'_t \overset{d_t}{\geq} \sigma_t$ if and only if $d'_t(x_t, \varepsilon_t) \geq d_t(x_t, \varepsilon_t)$ for all x_t, ε_t. Notice that $\sigma'_t \overset{d_t}{\geq} \sigma_t$ implies:

$$\int_0^{\hat{k}_t} f_i^{\sigma_t}(x_{t+1}|x_t, d_{it}, \hat{c}_{it}) - f_i^{\sigma'_t}(x_{t+1}|x_t, d_{it}, \hat{c}_{it})\, d\bar{k}_t \geq 0$$

for all $\hat{k}_t \in [0,1]$. This is equivalent to saying that $Pr(\bar{k}_t < \hat{k}_t|x_t, d_{it}, \hat{c}_{it};\sigma_t) \geq Pr(\bar{k}_t < \hat{k}_t|x_t, d_{it}, \hat{c}_{it};\sigma'_t)$. In other words, the distribution of $\bar{k}_t$ under strategy set σ_t' first order stochastically dominates the distribution of $\bar{k}_t$ under strategy set σ_t. In other words, higher levels of $\bar{k}_t$ become more likely and lower levels of $\bar{k}_t$ become less likely. Notice that no restrictions are imposed on the distribution of the remaining part of vector x_{t+1}.

I aim to show that at constant $d_{it} \in \{0,1\}$ and at any possible choice A_{it+1}, for any $\lambda > 0$, there exists a threshold $\psi > 0$ such that, for $|\phi| \leq \psi$, then the following inequality holds:

$$\left| \frac{\partial v_i\left(d_{it}, c_{it}^d, x_t; \sigma_t'\right)}{\partial A_{it+1}} - \frac{\partial v_i\left(d_{it}, c_{it}^d, x_t; \sigma_t\right)}{\partial A_{it+1}} \right| \leq \lambda$$

for all states x_t and all σ_t', σ_t. Define the vector $z_{t+1} = \left\{a_{t+1,}, A_{-it+1}, y_{t+1}, k_t, \bar{k}_t, price_{t+1}, \xi_{t+1}\right\}$ where $A_{it+1} \notin z_{t+1}$. Now rewrite $v_i\left(d_{it}, c_{it}^d, x_t; \sigma_t\right)$ as follows:

$$v_i\left(d_{it}, c_{it}^d, x_t; \sigma_t\right) = u_{it}^d + \beta \int\limits_{z_{t+1}} \int\limits_{A_{it+1}} V(x_{t+1}; \sigma_{t+1})\, f_i^{\sigma_t}\left(x_{t+1}|x_t, d_{it}, \hat{c}_{it}\right) dA_{it+1}\, dz_{t+1}$$

because A_{it+1} is deterministic, i.e., $f_i^{\sigma_t}\left(x_{t+1}|x_t, d_{it}, \hat{c}_{it}\right) > 0$ if $A_{it+1} = \hat{A}_{it+1}$ and zero otherwise, and it does not affect the transition probability of any state in z_{t+1}, it is possible to show that:

$$v_i\left(d_{it}, c_{it}^d, x_t; \sigma_t\right) = u_{it}^d + \beta \int\limits_{z_{t+1}} V(\hat{x}_{t+1}; \sigma_{t+1})\, f_i^{\sigma_t}\left(\hat{x}_{t+1}|x_t, d_{it}, \hat{c}_{it}\right) dz_{t+1}$$

where $\hat{x}_{t+1} = \{a_{t+1}, \hat{A}_{t+1,} y_{t+1}, k_t, \bar{k}_t, price_{t+1}, \xi_{t+1}\}$ and $\hat{A}_{t+1} = \{A_{1t+1}, A_{2t+1}, ..., \hat{A}_{it+1}, ...A_{n,t+1}\}$. Now taking the partial derivative with respect to A_{it+1} at $A_{it+1} = \hat{A}_{it+1}$:

$$[A_{it+1}]_{\hat{A}_{it+1}, d_{it}} = u_{it,c}^d + \beta \int\limits_{z_{t+1}} \left[\frac{\partial}{\partial A_{it+1}} V(\hat{x}_{t+1}; \sigma_{t+1})\right] f_i^{\sigma_t}\left(\hat{x}_{t+1}|x_t, d_{it}, \hat{c}_{it}\right)\, dz_{t+1}$$

It is useful to show how this formula differs in the case when $d_{it} = 0$ and $d_{it} = 1$:

$$\begin{aligned}
[A_{it+1}]_{A_{it+1}, d_{it}=0} = & -\nu\left[(1+r)A_{it} - A_{it+1} + y_{it}\right]^{\nu-1}\left(1 + \eta k_{it-1} + \phi \bar{k}_{t-1}\right) \\
& + \beta \int_{x_{t+1}} \Big\{\hat{u}_{it+1,c}^0 (1+r)[1 - p^{\sigma_{t+1}}(d_{it+1} = 1|x_{t+1})] + \hat{u}_{it+1,c}^1 (1+r)\left[p^{\sigma_{t+1}}(d_{it+1} = 1|x_{t+1})\right] \\
& + P'(v_{it+1}^1 - v_{it+1}^0)[v_i(d_{it+1} = 1, c_{it+1}^1, x_{t+1}; \sigma_{t+1}) - v_i(d_{it+1} = 0, c_{it+1}^0, x_{t+1}; \sigma_{t+1})] \\
& \cdot (1 + \eta k_{it} + \phi \bar{k}_t)(1+r)\nu\left[\left(c_{it+1}^1\right)^{\nu-1} - \left(c_{it+1}^0\right)^{\nu-1}\right]\Big\}\, f_i^{\sigma_t}\left(x_{t+1}|x_t, 0, \hat{c}_{it}\right) dx_{t+1}
\end{aligned}$$

and similarly for $v_{it}^{1}\,(d_{it}=1)$:

$$[A_{it+1}]_{A_{it+1},d_{it}=1}=-\nu\left[(1+r)A_{it}-A_{it+1}-price_t+y_{it}\right]^{\nu-1}(1+\eta k_{it-1}+\phi\bar{k}_{t-1})+$$

$$+\beta\int_{x_{t+1}}\hat{u}_{it+1,c}^{1}(1+r)\,f_i^{\sigma_t}\left(x_{t+1}|x_t,1,\hat{c}_{it}\right)dx_{t+1}$$

Now consider the derivative of $v_i\left(d_{it},c_{it}^{d},x_t;\sigma_t\right)$ with respect to A_{it+1}:

$$[A_{it+1}]=-\hat{u}_{it,c}^{d}+\beta\int\limits_{z+1}\frac{\partial}{\partial A_{it+1}}\left[V_i(x_{t+1};\sigma_{t+1})\right]f_i^{\sigma_t}\left(x_{t+1}|x_t,d_{it},\hat{c}_{it}\right)dz_{t+1}$$

Notice that the 'time to build' assumption makes $\hat{u}_{it,c}$ independent of other households' adoption choice at time t. Moreover, the Markov property implies that, $p^{\sigma_{t+1}}(d_{it+1}=1|x_{t+1})$ is independent of d_{it},c_{it},x_t given x_{t+1}. Lastly, the envelope condition makes $\frac{\partial}{\partial A_{it+1}}\left[V_i(x_{t+1};\sigma_{t+1})\right]$ independent of the value function in period $t+2$ and the subsequent ones. Thus, for a household $\frac{\partial}{\partial A_{it+1}}\left[V_i(x_{t+1};\sigma_{t+1})\right]$ is independent of σ_t. Then

$$[A_{it+1}]^{\sigma_t'}-[A_{it+1}]^{\sigma_t}=\beta\int\limits_{z_{t+1}}\left\{\frac{\partial V_i(x_{t+1};\sigma_{t+1})}{\partial A_{it+1}}\left[f_i^{\sigma_t'}\left(x_{t+1}|x_t,d_{it},\hat{c}_{it}\right)-f_i^{\sigma_t}\left(x_{t+1}|x_t,d_{it},\hat{c}_{it}\right)\right]\right\}dz_{t+1}$$

Now define the vector $w_{t+1}=\{a_{t+1},A_{-it+1},y_{t+1},k_t,price_{t+1},\xi_{t+1}\}$ where $\bar{k}_t,A_{it+1}\notin w_{t+1}$. Notice that the envelope condition and the Markov Property imply that $\frac{\partial V_i(x_{t+1};\sigma_{t+1})}{\partial A_{it+1}}$ is invariable in all the elements of vector w_{t+1}. It is possible to rewrite:

$$[A_{it+1}]^{\sigma_t'}-[A_{it+1}]^{\sigma_t}=\beta\int\limits_{w_{t+1}}\int\limits_{\bar{k}_t}\left\{\frac{\partial V_i(x_{t+1};\sigma_{t+1})}{\partial A_{it+1}}\left[f_i^{\sigma_t'}\left(x_{t+1}|x_t,d_{it},\hat{c}_{it}\right)-f_i^{\sigma_t}\left(x_{t+1}|x_t,d_{it},\hat{c}_{it}\right)\right]\right\}d\bar{k}_t\,dw_{t+1}$$

Using integration by parts we get:

$$=\beta\int_{w_{t+1}}\left\{\left[\int_0^1 f_i^{\sigma_t'}\left(x_{t+1}|x_t,d_{it},\hat{c}_{it}\right)-f_i^{\sigma_t}\left(x_{t+1}|x_t,d_{it},\hat{c}_{it}\right)d\bar{k}_t\right]\frac{\partial}{\partial A_{it+1}}\left[V_i(\bar{x}_{t+1};\sigma_{t+1})\right]\right.$$

$$\left.-\int_0^1\left[\int_0^{\bar{k}_t} f_i^{\sigma_t'}\left(x_{t+1}|x_t,d_{it},\hat{c}_{it}\right)-f_i^{\sigma_t}\left(x_{t+1}|x_t,d_{it},\hat{c}_{it}\right)ds\right]\frac{\partial^2 V_i(x_{t+1};\sigma_{t+1})}{\partial A_{it+1}\partial\bar{k}_{t-1}}d\bar{k}_t\right\}dw_{t+1}$$

$$=\beta\int_{w_{t+1}}\frac{\partial^2 V_i(x_{t+1};\sigma_{t+1})}{\partial A_{it+1}\partial\bar{k}_{t-1}}\left[\int_0^{\bar{k}_t} f_i^{\sigma_t}\left(x_{t+1}|x_t,d_{it},\hat{c}_{it}\right)-f_i^{\sigma_t'}\left(x_{t+1}|x_t,d_{it},\hat{c}_{it}\right)ds\right]dw_{t+1}$$

$$=\beta\int_{w_{t+1}}\frac{\partial^2 V_i(x_{t+1};\sigma_{t+1})}{\partial A_{it+1}\partial\bar{k}_{t-1}}r_i^{\sigma_t,\sigma_t'}\left(x_{t+1}|x_t,d_{it},\hat{c}_{it}\right)dw_{t+1}$$

Notice that the above is equal to zero if $\frac{\partial^2 V_i(x_{t+1};\sigma_{t+1})}{\partial A_{it+1}\partial \bar{k}_{t-1}}$ is equal to zero as well.

CASE 1: $k_{it-1} = 0$.

$$\frac{\partial^2 V_i(x_{t+1};\sigma_{t+1})}{\partial A_{it+1}\partial \bar{k}_{t-1}} = \Bigg\{ \Bigg[(1+r) \Bigg[\nu \left(c^1_{it+1}\right)^{\nu-1} \phi + (\nu-1)\nu \left.\frac{dA^*_{it+2}}{d\bar{k}_t}\right|_{d_{it+1}=0} \left(c^0_{it+1}\right)^{\nu-2} (1+\phi\bar{k}_t) \Bigg] \Bigg] \left[1 - p^{\sigma_{t+1}}(d_{it+1}=1|x_{t+1})\right]$$

$$+ \Bigg[(1+r) \Bigg[\nu \left(c^1_{it+1}\right)^{\nu-1} \phi + (\nu-1)\nu \left.\frac{dA^*_{it+2}}{d\bar{k}_t}\right|_{d_{it+1}=1} \left(c^1_{it+1}\right)^{\nu-2} (1+\phi\bar{k}_t) \Bigg] \Bigg] \left[p^{\sigma_{t+1}}(d_{it+1}=1|x_{t+1})\right]$$

$$+P'(v^1_{it+1} - v^0_{it+1}) \left[\hat{u}^1_{it+1,c} - \hat{u}^0_{it+1,c}\right] (1+r)\cdot$$

$$\Bigg\{ \phi \left[\left(c^1_{it+1}\right)^{\nu} - \left(c^0_{it+1}\right)^{\nu} \right] + \Bigg(\hat{u}^1_{it+1,c} \left.\frac{dA^*_{it+2}}{d\bar{k}_t}\right|_{d_{it+1}=1} - \hat{u}^0_{it+1,c} \left.\frac{dA^*_{it+2}}{d\bar{k}_t}\right|_{d_{it+1}=0} \Bigg) \Bigg\}$$

$$+P'(v^1_{it+1} - v^0_{it+1})(1+r) \Bigg\{ \phi \left[\nu \left(c^1_{it+1}\right)^{\nu-1} - \nu \left(c^0_{it+1}\right)^{\nu-1} \right]$$

$$+ \Bigg(\hat{u}^1_{it+1,cc} \left.\frac{dA^*_{it+2}}{d\bar{k}_t}\right|_{d_{it+1}=1} - \hat{u}^0_{it+1,cc} \left.\frac{dA^*_{it+2}}{d\bar{k}_t}\right|_{d_{it+1}=1} \Bigg) \Bigg\}$$

$$+P'(v^1_{it+1} - v^0_{it+1}) \Bigg\{ \phi(1+\phi\bar{k}_t)(1+r)\nu^2 \left[\left(c^1_{it+1}\right)^{\nu-1} - \left(c^0_{it+1}\right)^{\nu-1} \right] \left[\left(c^1_{it+1}\right)^{\nu} - \left(c^0_{it+1}\right)^{\nu} \right] + (1+\phi\bar{k}_t)(1+r)\nu \left[\left(c^1_{it+1}\right)^{\nu-1} - \left(c^0_{it+1}\right)^{\nu-1} \right] \Bigg[\hat{u}^1_{it+1,c} \left.\frac{dA^*_{it+2}}{d\bar{k}_t}\right|_{d_{it+1}=1} - \hat{u}^0_{it+1,c} \left.\frac{dA^*_{it+2}}{d\bar{k}_t}\right|_{d_{it+1}=0} \Bigg] \Bigg\}$$

$$+P''(v^1_{it+1} - v^0_{it+1}) \cdot [v^1_{it+1} - v^0_{it+1}] \Bigg\{ \phi(1+\phi\bar{k}_t)(1+r)\nu \left[\left(c^1_{it+1}\right)^{\nu-1} - \left(c^0_{it+1}\right)^{\nu-1} \right] \left[\left(c^1_{it+1}\right)^{\nu} - \left(c^0_{it+1}\right)^{\nu} \right] + (1+\phi\bar{k}_t)(1+r)\nu \left[\left(c^1_{it+1}\right)^{\nu-1} - \left(c^0_{it+1}\right)^{\nu-1} \right] \Bigg[\hat{u}^1_{it+1,c} \left.\frac{dA^*_{it+2}}{d\bar{k}_t}\right|_{d_{it+1}=1} - \hat{u}^0_{it+1,c} \left.\frac{dA^*_{it+2}}{d\bar{k}_t}\right|_{d_{it+1}=0} \Bigg] \Bigg\}$$

CASE 2: $k_{it-1} = 1$. The above simplifies because $p^{\sigma_{t+1}}(d_{it+1} = 1|x_{t+1}) = 0$ thus:

$$\frac{\partial^2 V_i(x_{t+1};\sigma_{t+1})}{\partial A_{it+1}\partial \bar{k}_{t-1}} = (1+r) \Bigg\{ \nu \left[c^0_{it+1}\right]^{\nu-1} \phi + (\nu-1)\nu \left.\frac{dA^*_{it+2}}{d\bar{k}_t}\right|_{d_{it+1}=0} \left[c^0_{it+1}\right]^{\nu-2} (1+\eta+\phi\bar{k}_t) \Bigg\}$$

CASE 3: for $d_{it} = 1$ one gets (for any k_{it-1}):

$$\frac{\partial^2 V_i(x_{t+1};\sigma_{t+1})}{\partial A_{it+1}\partial \bar{k}_{t-1}} = (1+r) \Bigg\{ \nu \left[c^0_{it+1}\right]^{\nu-1} \phi + (\nu-1)\nu \left.\frac{dA^*_{it+2}}{d\bar{k}_t}\right|_{d_{it+1}=1} \left[c^0_{it+1}\right]^{\nu-2} (1+\eta+\phi\bar{k}_t) \Bigg\}$$

Now notice that if $\phi = 0$ then the cross derivative for $d_{it} = 0$ becomes:

For **CASE 1:** $k_{it-1} = 0$:

$$[A_{it+1}]^{\sigma_t'} - [A_{it+1}]^{\sigma_t} = \beta \int_{x_{t+1}} \left[\!\!\left[\left[(1+r)(\nu-1)\nu \left.\frac{dA^*_{it+2}}{d\bar{k}_t}\right|_{d_{it+1}=0} \left[c^0_{it+1}\right]^{\nu-2} \right] [1 - p^{\sigma_{t+1}}(d_{it+1} = 1|x_{t+1})] \right.\right.$$

$$+ \left[(1+r)(\nu-1)\nu \left.\frac{dA^*_{it+2}}{d\bar{k}_t}\right|_{d_{it+1}=1} \left[c^0_{it+1}\right]^{\nu-2} \right] [p^{\sigma_{t+1}}(d_{it+1} = 1|x_{t+1})]$$

$$+ P'(v^1_{it+1} - v^0_{it+1}) \left[\hat{u}^1_{it+1,c} - \hat{u}^0_{it+1,c}\right] (1+r) \left[\hat{u}^1_{it+1,c} \left.\frac{dA^*_{it+2}}{d\bar{k}_t}\right|_{d_{it+1}=1} - \hat{u}^0_{it+1,c} \left.\frac{dA^*_{it+2}}{d\bar{k}_t}\right|_{d_{it+1}=0} \right]$$

$$+ P'(v^1_{it+1} - v^0_{it+1})(1+r) \left[\hat{u}^1_{it+1,cc} \left.\frac{dA^*_{it+2}}{d\bar{k}_t}\right|_{d_{it+1}=1} - \hat{u}^0_{it+1,cc} \left.\frac{dA^*_{it+2}}{d\bar{k}_t}\right|_{d_{it+1}=1} \right]$$

$$+ P'(v^1_{it+1} - v^0_{it+1})(1+r)\nu \left[\left(c^1_{it+1}\right)^{\nu-1} - \left(c^0_{it+1}\right)^{\nu-1} \right] \left[\hat{u}^1_{it+1,c} \left.\frac{dA^*_{it+2}}{d\bar{k}_t}\right|_{d_{it+1}=1} - \hat{u}^0_{it+1,c} \left.\frac{dA^*_{it+2}}{d\bar{k}_t}\right|_{d_{it+1}=0} \right]$$

$$+ P''(v^1_{it+1} - v^0_{it+1})[v^1_{it+1} - v^0_{it+1}](1+r)\nu \left[\left(c^1_{it+1}\right)^{\nu-1} - \left(c^0_{it+1}\right)^{\nu-1} \right]$$

$$\left.\left. \cdot \left[\hat{u}^1_{it+1,c} \left.\frac{dA^*_{it+2}}{d\bar{k}_t}\right|_{d_{it+1}=1} - \hat{u}^0_{it+1,c} \left.\frac{dA^*_{it+2}}{d\bar{k}_t}\right|_{d_{it+1}=0} \right] \right]\!\!\right] r_i^{\sigma_t, \sigma_t'} (x_{t+1}|x_t, 0, \hat{c}_{it})\, dx_{t+1}$$

For **CASE 2:** $k_{it-1} = 1$, the difference $[A_{it+1}]^{\sigma_t'} - [A_{it+1}]^{\sigma_t}$ becomes:

$$[A_{it+1}]^{\sigma_t'} - [A_{it+1}]^{\sigma_t} = \beta \int\limits_{x_{t+1}} (1+r)(\nu-1)\nu \left.\frac{dA^*_{it+2}}{d\bar{k}_t}\right|_{d_{it+1}=0} \left[c^0_{it+1}\right]^{\nu-2} (1+\eta)\, r_i^{\sigma_t, \sigma_t'} (x_{t+1}|x_t, 0, \hat{c}_{it})\, dx_{t+1}$$

and similarly for **CASE 3** ($d_{it} = 1$) the difference $[A_{it+1}]^{\sigma_t'} - [A_{it+1}]^{\sigma_t}$ becomes:

$$[A_{it+1}]^{\sigma_t'} - [A_{it+1}]^{\sigma_t} = \beta(1+r) \int\limits_{x_{t+1}} (\nu-1)\nu \left.\frac{dA^*_{it+2}}{d\bar{k}_t}\right|_{d_{it+1}=1} \left[c^0_{it+1}\right]^{\nu-2} (1+\eta)\, r_i^{\sigma_t, \sigma_t'} (x_{t+1}|x_t, 1, \hat{c}_{it})\, dx_{t+1}$$

These differences are both zero if $\left.\frac{dA^*_{it+2}}{d\bar{k}_t}\right|_{A_{it+1}, d_{it+1}, k_{it}, A_{it}} = 0$ for all $d_{it+1} \in \{0, 1\}$. When is this the case? If A^*_{it+2} is not an interior solution, then the derivative is always zero. If it is interior, consider the FOC w.r.t A_{it+2} in period $t+1$.

When is this the case?

$$[A_{it+2}]_{A_{it+2},d_{it+1}=0} = -\nu\left[(1+r)A_{it+1} - A_{it+2} + y_{it+1}\right]^{\nu-1}(1+\eta k_{it} + \phi\bar{k}_t)$$

$$+\beta\int_{x_{t+2}}\left\{\hat{u}^0_{it+2,c}(1+r)[1-p^{\sigma_{t+2}}(d_{it+2}=1|x_{t+2})] + \hat{u}^1_{it+2,c}(1+r)p^{\sigma_{t+2}}(d_{it+2}=1|x_{t+2})\right.$$

$$+P'(v^1_{it+2} - v^0_{it+2})[v_i(1,c^1_{it+2},x_{t+2};\sigma_{t+2}) - v_i(0,c^0_{it+2},x_{t+2};\sigma_{t+2})](1+\eta k_{it+1} + \phi\bar{k}_{t+1})$$

$$\left.\cdot(1+r)\nu\left[\left(c^1_{it+2}\right)^{\nu-1} - \left(c^0_{it+2}\right)^{\nu-1}\right]\right\} f_i^{\sigma_{t+1}}(x_{t+2}|x_{t+1},d_{it+1},\hat{c}_{it+1})\,dx_{t+2}$$

At an interior solution the FOC must be satisfied with equality. Now totally differentiate w.r.t $\bar{k}_t$.

$$[A_{it+2},\bar{k}_t]_{A_{it+2},d_{it+1}=0} = -\nu\left[c^d_{it+1}\right]^{\nu-1}\phi + (1-\nu)\nu\left[c^d_{it+1}\right]^{\nu-2}\left.\frac{dA^*_{it+2}}{d\bar{k}_t}\right|_{d_{it+1}}$$

$$+\beta\int_{x_{t+2}}\frac{\partial V_i(x_{t+2};\sigma_{t+2})}{\partial A_{it+2}}\frac{\partial}{\partial\bar{k}_t}\left[f_i^{\sigma_{t+1}}(x_{t+2}|x_{t+1},d_{it},\hat{c}_{it})\right]$$

$$+\frac{\partial^2 V_i(x_{t+2};\sigma_{t+2})}{\partial A^2_{it+2}}\left.\frac{dA^*_{it+2}}{d\bar{k}_t}\right|_{d_{it+1}} f_i^{\sigma_{t+1}}(x_{t+2}|x_{t+1},d_{it},\hat{c}_{it})\,dx_{t+2}$$

$$\int_{x_{t+2}}\frac{\partial V_i(x_{t+2};\sigma_{t+2})}{\partial A_{it+2}}\frac{\partial}{\partial\bar{k}_t}\left[f_i^{\sigma_t}(x_{t+2}|x_{t+1},d_{it},\hat{c}_{it})\right]dx_{t+2}$$

$$= \int_{w_{t+2}}\int_{\bar{k}_{t+1}}\frac{\partial V_i(x_{t+2};\sigma_{t+2})}{\partial A_{it+2}}\frac{\partial}{\partial\bar{k}_t}\left[f_i^{\sigma_{t+1}}(x_{t+2}|x_{t+1},d_{it},\hat{c}_{it})\right]d\bar{k}_{t+1}\,dw_{t+2}$$

Using this result, it is possible to write:

$$\beta\int_{x_{t+2}}\frac{\partial V_i(x_{t+2};\sigma_{t+2})}{\partial A_{it+2}}\frac{\partial}{\partial\bar{k}_t}\left[f_i^{\sigma_{t+1}}(x_{t+2}|x_{t+1},d_{it},\hat{c}_{it})\right]dx_{t+2}$$

$$= \beta\int_{w_{t+2}}\frac{\partial V_i(\bar{x}_{t+2};\sigma_{t+2})}{\partial A_{it+2}}\int_{\bar{k}_{t+1}}\frac{\partial}{\partial\bar{k}_t}\left[f_i^{\sigma_{t+1}}(x_{t+2}|x_{t+1},d_{it},\hat{c}_{it})\right]d\bar{k}_{t+1}$$

$$-\int_{\bar{k}_{t+1}}\frac{\partial^2 V_i(x_{t+2};\sigma_{t+2})}{\partial A_{it+2}\partial\bar{k}_{t+1}}\int_{\underline{k}}^{\bar{k}_{t+1}}\frac{\partial}{\partial\bar{k}_t}\left[f_i^{\sigma_{t+1}}(x_{t+2}|x_{t+1},d_{it},\hat{c}_{it})\right]d\bar{k}_{t+1}dw_{t+2}$$

Now notice that, at constant A_{it+2} we get that $\int_{\bar{k}_{t+1}}\left[f_i^{\sigma_{t+1}}(x_{t+2}|x_{t+1},d_{it},\hat{c}_{it})\right]d\bar{k}_{t+1} = s(w_{t+2}|d_{it},\hat{c}_{it})$ that is independent of x_{t+1}. The intuition here is that the Envelope condition and the Markov property imply that $\frac{\partial V_i(x_{t+2};\sigma_{t+2})}{\partial A_{it+2}}$ is invariable in all the elements of vector w_{t+2}. Thus it is possible to write:

$$\beta\int_{w_{t+2}}\frac{\partial V_i(\bar{x}_{t+2};\sigma_{t+2})}{\partial A_{it+2}}\int_{\bar{k}_{t+1}}\frac{\partial}{\partial\bar{k}_t}\left[f_i^{\sigma_{t+1}}(x_{t+2}|x_{t+1},d_{it},\hat{c}_{it})\right]d\bar{k}_{t+1}\,dw_{t+2}$$

$$= \beta\frac{\partial V_i(\bar{x}_{t+2};\sigma_{t+2})}{\partial A_{it+2}}\frac{\partial}{\partial\bar{k}_t}\int_{w_{t+2}}\int_{\bar{k}_{t+1}}\left[f_i^{\sigma_{t+1}}(x_{t+2}|x_{t+1},d_{it},\hat{c}_{it})\right]d\bar{k}_{t+1} = 0$$

The above becomes:

$$-\beta \int\limits_{w_{t+2}} \frac{\partial^2 V_i(x_{t+2};\sigma_{t+2})}{\partial A_{it+2}\partial \bar{k}_{t+1}} \int\limits_{\underline{k}}^{\bar{k}_{t+1}} \frac{\partial}{\partial \bar{k}_t} \left[f_i^{\sigma_{t+1}} \left(x_{t+2}|x_{t+1}, d_{it}, \hat{c}_{it} \right) \right] d\bar{k}_{t+1} \, dw_{t+2}$$

Notice that if the optimal solution for A^*_{it+2} is interior, it is possible to calculate the following:

$$\left.\frac{dA^*_{it+2}}{d\bar{k}_t}\right|_{d_{it+1}} = \frac{\nu \left[c^d_{it+1}\right]^{\nu-1} \phi - \beta \int_{x_{t+2}} \frac{\partial^2 V_i(x_{t+2};\sigma_{t+2})}{\partial A_{it+2}\partial \bar{k}_{t+1}} \int_{\underline{k}}^{\bar{k}_{t+1}} \frac{\partial}{\partial \bar{k}_t} \left[f_i^{\sigma_{t+1}} \left(x_{t+2}|x_{t+1}, d_{it}, \hat{c}_{it} \right) \right] d\bar{k}_{t+1} \, dx_{t+2}}{(1-\nu)\nu \left[c^d_{it+1}\right]^{\nu-2} + (1-\nu)\nu \left[c^d_{t+1}\right]^{\nu-2} + \beta \int_{x_{t+2}} \frac{\partial^2 V_i(x_{t+2};\sigma_{t+2})}{\partial A^2_{it+2}} f_i^{\sigma_{t+1}} \left(x_{t+2}|x_{t+1}, d_{it}, \hat{c}_{it} \right) dx_{t+2}}$$

which is equal to zero if ϕ and $\frac{\partial^2 V_i(x_{t+2};\sigma_{t+2})}{\partial A_{it+2}\partial \bar{k}_{t+1}} = 0$. But under those conditions, one can update $[A_{it+1}]^{\sigma'_t} - [A_{it+1}]^{\sigma_t}$ and conclude that $[A_{it+1}]^{\sigma'_t} - [A_{it+1}]^{\sigma_t} = 0$ if $[A_{it+2}]^{\sigma'_{t+1}} - [A_{it+2}]^{\sigma_{t+1}}$ at any state vector that can be reached with positive probability from x_t with choices A_{it+1}, d_{it}. This updating process can go on recursively until period $T-1$ (i.e., $\mathcal{A}-1$) at that point notice that $\left.\frac{dA^*_{iT+1}}{d\bar{k}_{T-1}}\right|_{d_{iT-1}} = 0$ because in the last period of life T (i.e., $\mathcal{A}$) households consumer all such that $A^*_{iT+1} = 0$. This implies that $[A_{iT+1}, \bar{k}_T]_{d_{iT}, k_{iT-1}=0} := 0$ (i.e., household's savings is unaffected by $\bar{k}_T$ because they do not save in any case). Therefore recursively $[A_{iT+1-s}, \bar{k}_{T-s}]_{d_{iT-s}, k_{iT-1-s}=0} := 0$ for all $s \in [0, 1, ...T]$. Notice that if the solution for A^*_{it+2} is not interior, then $\left.\frac{dA^*_{it+2}}{d\bar{k}_t}\right|_{d_{it+1}} = 0$ and the desired result hold trivially. Lastly, notice that, because $[A_{it+1}]^{\sigma'_t} - [A_{it+1}]^{\sigma_t}$ is continuous in ϕ and with finite derivative, then for any $\lambda > 0$ there exists ψ such that if $\phi \leq \psi$ then $[A_{it+1}]^{\sigma'_t} - [A_{it+1}]^{\sigma_t} \leq \lambda$. I define $\psi(\lambda, d_{it}, A_{it+1}, x_t, \sigma_t)$ to be the minimum ψ that ensures that the inequality is satisfied at specific values of states and controls $d_{it}, A_{it+1}, x_t, \sigma_t$.

D.1.2 i-Increasing Differences in d_{it}, σ_t

To show that $v_t(d_{it}=1, c^1_{it}, x_t; \sigma_t) - v_t(d_{it}=0, c^0_{it}, x_t; \sigma_t)$ is increasing in σ_t. Recall that the value functions are expressed as:

$$v_i\left(d_{it}=1, c^1_{it}, x_t; \sigma_t\right) = \left[(1+r)A_{it} - A_{it+1} + y_{it} - price_t\right]^{\nu}\left(1 + \eta k_{it-1} + \phi \bar{k}_{t-1}\right) + \alpha k_{it-1} + \gamma k_{it-1}\bar{k}_{t-1}$$
$$+\beta \int_{x_{t+1}} V_{t+1}(x_{t+1}; \sigma_{t+1})\, f_i^{\sigma_t}\left(x_{t+1}|x_t, 1, \hat{c}_{it}\right) dx_{t+1}$$

$$v_i\left(d_{it}=0, c^0_{it}, x_t; \sigma_t\right) = \left[(1+r)A_{it} - A_{it+1} + y_{it}\right]^{\nu}\left(1 + \eta k_{it-1} + \phi \bar{k}_{t-1}\right) + \alpha k_{it-1} + \gamma k_{it-1}\bar{k}_{t-1}$$
$$+\beta \int_{x_{t+1}} V_{t+1}(x_{t+1}; \sigma_{t+1})\, f_i^{\sigma_t}\left(x_{t+1}|x_t, 0, \hat{c}_{it}\right) dx_{t+1}$$

Thus

$$\left\{\left[v_i\left(d_{it}=1, c^1_{it}, x_t; \sigma'_t\right) - v_i\left(d_{it}=0, c^0_{it}, x_t; \sigma'_t\right)\right] - \left[v_i\left(d_{it}=1, c^1_{it}, x_t; \sigma_t\right) - v_i\left(d_{it}=0, c^0_{it}, x_t; \sigma_t\right)\right]\right\}_{A_{it+1}}$$

$$= \beta \int_{x_{t+1}} V_i(x_{t+1}; \sigma_{t+1})\, f_i^{\sigma'_t}\left(x_{t+1}|x_t, 1, \hat{c}_{it}\right) - V_i(x_{t+1}; \sigma_{t+1})\, f_i^{\sigma'_t}\left(x_{t+1}|x_t, 0, \hat{c}_{it}\right)$$
$$- V_i(x_{t+1}; \sigma_{t+1})\, f_i^{\sigma_t}\left(x_{t+1}|x_t, 1, \hat{c}_{it}\right) + V_i(x_{t+1}; \sigma_{t+1})\, f_i^{\sigma_t}\left(x_{t+1}|x_t, 0, \hat{c}_{it}\right) dx_{t+1}$$

because of the assumption that $\bar{k}_t$ is unaffected by d_{it} on the point of view of household i, then for a given A_{it+1}, and the fact that k_{it} is a deterministic state, it is possible to write:

$$\beta \int_{q_{t+1}} \int_{\bar{k}_t} \left[V_i(x'_{t+1}; \sigma_{t+1}) - V_i(x_{t+1}; \sigma_{t+1})\right] \left[f_i^{\sigma'_t}\left(x_{t+1}|x_t, d_{it}, \hat{c}_{it}\right) - f_i^{\sigma_t}\left(x_{t+1}|x_t, d_{it}, \hat{c}_{it}\right)\right] d\bar{k}_t\, dq_{t+1}$$

$$= \beta \int_{q_{t+1}} \left[V_i(x'_{t+1}; \sigma_{t+1}) - V_i(x_{t+1}; \sigma_{t+1})\right] \int_{\bar{k}_t} \left[f_i^{\sigma'_t}\left(x_{t+1}|x_t, d_{it}, \hat{c}_{it}\right) - f_i^{\sigma_t}\left(x_{t+1}|x_t, d_{it}, \hat{c}_{it}\right)\right] d\bar{k}_t$$

$$+ \int_{q_{t+1}} \frac{\partial\left[V_i(x'_{t+1}, \sigma_{t+1}) - V_i(x_{t+1}, \sigma_{t+1})\right]}{\partial \bar{k}_t} r_i^{\sigma_t, \sigma'_t}\left(x_{t+1}|x_t, d_{it}, \hat{c}_{it}\right) dq_{t+1}$$

where $r_i^{\sigma_t, \sigma'_t}\left(x_{t+1}|x_t, d_{it}, \hat{c}_{it}\right) \geq 0$ for all x_{t+1}

$$= \beta \int_{x_{t+1}} \frac{\partial\left[V_i(x'_{t+1}, \sigma_{t+1}) - V_i(x_{t+1}, \sigma_{t+1})\right]}{\partial \bar{k}_t} r_i^{\sigma_t, \sigma'_t}\left(x_{t+1}|x_t, d_{it}, \hat{c}_{it}\right) dx_{t+1}$$

$$= E_{r_t}\left[\frac{\partial\left[V_i(x'_{t+1}, \sigma_{t+1}) - V_i(x_{t+1}, \sigma_{t+1})\right]}{\partial \bar{k}_t}\right]$$

Assuming an interior solution at time $t+1$, it is possible to use the Envelope condition to calculate:

$$\frac{\partial\left[V_i(x'_{t+1},\sigma_{t+1})-V_i(x_{t+1},\sigma_{t+1})\right]}{\partial\bar{k}_t} = \phi\left(c^0_{it+1}(d_{it}=1)\right)^{\nu} + \gamma k_{it}(d_{it}=1)$$

$$+\gamma k_{it}(d_{it}=0) - \phi\left(c^0_{it+1}(d_{it}=0)\right)^{\nu}\left[p^{\sigma_{t+1}}(d_{it+1}=1|x_{t+1})\right]$$

$$-\phi\left(c^0_{it+1}(d_{it}=0)\right)^{\nu}\left[1-p^{\sigma_{t+1}}(d_{it+1}=1|x_{t+1})\right] - \gamma k_{it}(d_{it}=0)$$

$$-P'(v^1_{it+1}-v^0_{it+1})[v^1_{it+1}-v^0_{it+1}][\phi\left(c^0_{it+1}(d_{it}=1)\right)^{\nu} + \gamma k_{it}(d_{it}=1)$$

$$-\phi\left(c^0_{it+1}(d_{it}=0)\right)^{\nu}\left[p^{\sigma_{t+1}}(d_{it+1}=1|x_{t+1})\right]$$

$$-\phi\left(c^0_{it+1}(d_{it}=0)\right)^{\nu}\left[1-p^{\sigma_{t+1}}(d_{it+1}=1|x_{t+1})\right] - \gamma k_{it}(d_{it}=0)$$

For $\phi = 0$ this reduces to:

$$\frac{\partial\left[V_i(x'_{t+1},\sigma_{t+1})-V_i(x_{t+1},\sigma_{t+1})\right]}{\partial\bar{k}_t} = \left[1-P'(v^1_{it+1}-v^0_{it+1})[v^1_{it+1}-v^0_{it+1}]\right]\left[\gamma k_{it}(d_{it}=1)-\gamma k_{it}(d_{it}=0)\right]$$

Thus one gets that:

- If $k_{it-1}=1$ then $E_{r_t}\left[\frac{\partial\left[V_i(x'_{t+1},\sigma_{t+1})-V_i(x_{t+1},\sigma_{t+1})\right]}{\partial\bar{k}_t}\right]=0$
- If $k_{it-1}=0$ then $E_{r_t}\left[\frac{\partial\left[V_i(x'_{t+1},\sigma_{t+1})-V_i(x_{t+1},\sigma_{t+1})\right]}{\partial\bar{k}_t}\right]>0$ for $E_{r_t}\left[P'(v^1_{it+1}-v^0_{it+1})[v^1_{it+1}-v^0_{it+1}]\right]<1$, which is the case as long as $P(x)$ is "flat" enough.

The latter results implies that, for all households i it must be true that:

$$v_i\left(d'_{it},c^1_{it}(A'_{it+1}),x_t;\sigma'_t\right)-v_i\left(d'_{it},c^1_{it}(A'_{it+1}),x_t;\sigma_t\right)\geq v_i\left(d''_{it},c^1_{it}(A'_{it+1}),x_t;\sigma'_t\right)-v_i\left(d''_{it},c^1_{it}(A'_{it+1}),x_t;\sigma_t\right)$$

and the inequality is strict for all households j such that $k_{jt-1}=0$ i.e., the objective function satisfies *i-Increasing Differences* in d_{it},σ_t (see. Milgrom and Shannon 1994).

D.1.3 i-Highest and i-Lowest Equilibria

I want to show that for all i such that $k_{it-1} = 0$, the following holds:

$$v_i\left(d'_{it}, c^1_{it}(A'_{it+1}), x_t; \sigma'_t\right) - v_i\left(d''_{it}, c^1_{it}(A''_{it+1}), x_t; \sigma'_t\right) \geq v_i\left(d'_{it}, c^1_{it}(A'_{it+1}), x_t; \sigma_t\right) - v_i\left(d''_{it}, c^1_{it}(A''_{it+1}), x_t; \sigma_t\right) \tag{D.1}$$

holds for any A'_{it+1}, A''_{it+1} and for $d'_{it} > d''_{it}$ and $\sigma'_t \geq \sigma_t$, in the sense defined above.

Proof:

Suppose (D.1) is not satisfied i.e., the following instead is true:

$$v_i\left(d'_{it}, c^1_{it}(A'_{it+1}), x_t; \sigma'_t\right) - v_i\left(d''_{it}, c^1_{it}(A''_{it+1}), x_t; \sigma'_t\right) < v_i\left(d'_{it}, c^1_{it}(A'_{it+1}), x_t; \sigma_t\right) - v_i\left(d''_{it}, c^1_{it}(A''_{it+1}), x_t; \sigma_t\right) \tag{D.2}$$

The fact that $[A_{it+1}]^{\sigma'_t} - [A_{it+1}]^{\sigma_t} \leq \lambda$ for $0 < \phi \leq \psi(\lambda, d_{it}, A_{it+1}, x_t\sigma_t)$ implies that:

$$\begin{aligned}
&v_i\left(d'_{it}, c^1_{it}(A'_{it+1}), x_t; \sigma'_t\right) - v_i\left(d'_{it}, c^1_{it}(A''_{it+1}), x_t; \sigma'_t\right) \\
&\quad = v_i\left(d'_{it}, c^1_{it}(A'_{it+1}), x_t; \sigma_t\right) - v_i\left(d'_{it}, c^1_{it}(A''_{it+1}), x_t; \sigma_t\right) + b(d'_{it}, A'_{it+1}, A''_{it+1}, x_t; \sigma'_t, \sigma_t, \phi)
\end{aligned}$$

where b is a continuous function such that $b(d'_{it}, A'_{it+1}, A''_{it+1}, x_t; \sigma'_t, \sigma_t, \phi) \leq \zeta$ if $\phi \leq \psi(\lambda, d_{it}, A_{it+1}, x_t, \sigma_t)$. Because of the continuity (and finite derivative) of b, for any $\zeta > 0$ there exists $\bar{\phi}(\zeta, d_{it}, A_{it+1}, x_t, \sigma_t)$ such that if $0 < \phi \leq \bar{\phi}(\zeta, d_{it}, A_{it+1}, x_t, \sigma_t)$ then $|b| \leq \zeta$. This implies:

$$\begin{aligned}
&v_i\left(d'_{it}, c^1_{it}(A'_{it+1}), x_t; \sigma'_t\right) = v_i\left(d'_{it}, c^1_{it}(A''_{it+1}), x_t; \sigma'_t\right) \\
&\quad + v_i\left(d'_{it}, c^1_{it}(A'_{it+1}), x_t; \sigma_t\right) - v_i\left(d'_{it}, c^1_{it}(A''_{it+1}), x_t; \sigma_t\right) + b(d'_{it}, A'_{it+1}, A''_{it+1}, x_t; \sigma'_t, \sigma_t, \phi)
\end{aligned} \tag{D.3}$$

Similarly, one can get:

$$\begin{aligned}
&v_i\left(d''_{it}, c^1_{it}(A''_{it+1}), x_t; \sigma'_t\right) - v_i\left(d''_{it}, c^1_{it}(A'_{it+1}), x_t; \sigma'_t\right) \\
&\quad = v_i\left(d''_{it}, c^1_{it}(A''_{it+1}), x_t; \sigma_t\right) - v_i\left(d''_{it}, c^1_{it}(A'_{it+1}), x_t; \sigma_t\right) - b(d''_{it}, A'_{it+1}, A''_{it+1}, x_t; \sigma'_t, \sigma_t, \phi)
\end{aligned}$$

which implies:

$$v_i\left(d''_{it}, c^1_{it}(A''_{it+1}), x_t; \sigma'_t\right) = v_i\left(d''_{it}, c^1_{it}(A'_{it+1}), x_t; \sigma'_t\right)$$
$$+v_i\left(d''_{it}, c^1_{it}(A''_{it+1}), x_t; \sigma_t\right) - v_i\left(d''_{it}, c^1_{it}(A'_{it+1}), x_t; \sigma_t\right) - b(d''_{it}, A'_{it+1}, A''_{it+1}, x_t; \sigma'_t, \sigma_t, \phi) \tag{D.4}$$

Now substituting (D.3) and (D.4) into (D.2) we get:

$$v_i\left(d'_{it}, c^1_{it}(A''_{it+1}), x_t; \sigma'_t\right) - v_i\left(d'_{it}, c^1_{it}(A''_{it+1}), x_t; \sigma_t\right) + b(d'_{it}, A'_{it+1}, A''_{it+1}, x_t; \sigma'_t, \sigma_t, \phi)$$
$$-v_i\left(d''_{it}, c^1_{it}(A''_{it+1}), x_t; \sigma_t\right) + v_i\left(d''_{it}, c^1_{it}(A'_{it+1}), x_t; \sigma_t\right) + b(d''_{it}, A'_{it+1}, A''_{it+1}, x_t; \sigma'_t, \sigma_t, \phi) < 0$$

Now notice that $[A_{it+1}]^{\sigma'_t} - [A_{it+1}]^{\sigma_t} \leq \lambda$ implies that:

$$v_i\left(d'_{it}, c^1_{it}(A''_{it+1}), x_t; \sigma'_t\right) - v_i\left(d'_{it}, c^1_{it}(A''_{it+1}), x_t; \sigma_t\right)$$
$$= v_i\left(d'_{it}, c^1_{it}(A'_{it+1}), x_t; \sigma'_t\right) - v_i\left(d'_{it}, c^1_{it}(A'_{it+1}), x_t; \sigma_t\right) - b(d'_{it}, A'_{it+1}, A''_{it+1}, x_t; \sigma'_t, \sigma_t, \phi) \tag{D.5}$$

Substituting (D.5) into (D.2) and rearranging to get:

$$v_i\left(d'_{it}, c^1_{it}(A'_{it+1}), x_t; \sigma'_t\right) - v_i\left(d'_{it}, c^1_{it}(A'_{it+1}), x_t; \sigma_t\right)$$
$$< v_i\left(d''_{it}, c^1_{it}(A'_{it+1}), x_t; \sigma'_t\right) - v_i\left(d''_{it}, c^1_{it}(A'_{it+1}), x_t; \sigma_t\right) - b(d''_{it}, A'_{it+1}, A''_{it+1}, x_t; \sigma'_t, \sigma_t, \phi) \tag{D.6}$$

Recall that in the previous section it was shown that for all i such that $k_{it-1} = 0$ the following holds:

$$v_i\left(d'_{it}, c^1_{it}(A'_{it+1}), x_t; \sigma'_t\right) - v_i\left(d'_{it}, c^1_{it}(A'_{it+1}), x_t; \sigma_t\right) > v_i\left(d''_{it}, c^1_{it}(A'_{it+1}), x_t; \sigma'_t\right) - v_i\left(d''_{it}, c^1_{it}(A'_{it+1}), x_t; \sigma_t\right)$$

because v_i satisfies *i-Increasing Differences in* (d_{it}, σ'_t). We also know from the previous paragraph that or $0 < \phi \leq \bar{\phi}\left(\zeta, d_{it}, A_{it+1}, x_t, \sigma_t\right)$ we get $|b\left(d''_{it}, A'_{it+1}, A''_{it+1}, x_t; \sigma'_t, \sigma_t, \phi\right) \leq \zeta$. As this is the case for all $d_{it}, A_{it+1}, x_t, \sigma_t$ then there exists $\hat{\zeta}$ such that $|b\left(d''_{it}, A'_{it+1}, A''_{it+1}, x_t; \sigma'_t, \sigma_t, \phi\right)| \leq \hat{\zeta}$ for all $d_{it}, A_{it+1}, x_t, \sigma_t$. Then, if $\phi \leq \bar{\phi}\left(\hat{\zeta}\right)$, the condition (D.6) cannot be satisfied. This leads to a contradiction, Q.E.D

Now, because of this result, we know that for any higher beliefs $\sigma_t' \geq \sigma_t$, the best response for any household i implies (weakly) higher d_{it}. Thus with beliefs σ_t' all households play $d_{it} = 1$ with higher probability than under beliefs σ_t. As a result, if σ_t' and σ_t are equilibrium beliefs, then it must be that in equilibrium $\int_0^{\hat{k}_{it}} f_i^{\sigma_t}(x_{t+1}|x_t, d_{it}, \hat{c}_{it}) - f_i^{\sigma_t'}(x_{t+1}|x_t, d_{it}, \hat{c}_{it})\, d\bar{k}_t \geq 0$ for all $\hat{k}_t \in [\underline{k}_t, 1]$. It also implies that there exists a highest and a lowest pure strategy N.E. with respect to the distribution of $\bar{k}_t$.

E Tables

Table 5: First Stage Estimates: Earnings Function Parameters

Parameter	Coeff.	Std. Err	Variable Description
ψ_0^y	3.831	0.081	Constant
$\psi_{20\leq a<25}^y$	0.431	0.016	HH head Age $20 \leq a < 25$
$\psi_{25\leq a<50}^y$	0.824	0.009	HH head Age $25 \leq a < 50$
$\psi_{50\leq a<75}^y$	-0.106	0.004	HH head Age $50 \leq a < 75$
ψ_{edu1}^y	0.784	0.062	HH head Education (yrs)
ψ_{edu2}^y	-0.082	0.011	HH head Education Sq. (yrs)
$\psi_{age*edu3}^y$	0.110	0.015	HH Age x Education
σ_u^2	0.311	0.012	variance Innovations
σ_ξ^2	0.126	0.018	variance Measurement Error
ρ	1.00	-	presistence (Calibrated)

Notes: Parameter Estimates for the earnings function. Bootstrapped standard errors in parentheses.

Table 6: Structural Estimates: Preference Parameters

Parameter	Mod: No Borrowing ($A_t \geq 0$)	Mod: Borrowing Allowed	Description
ν	0.3376	0.3912	$(1-\nu)$ coeff of rel. risk aversion
η	0.00022	0.00018	interaction c_t & own sanitation
ϕ	0.00514	0.00482	interaction c_t & avg sanitation prev.
$\alpha_{20\leq a<26}$	4.8155	5.0569	imp. of sanitation 20≤age<26
$\alpha_{26\leq a<75}$	0.0138	0.0129	imp. of sanitation 26≤age<75
γ	2.7019	2.4233	interaction own sanitation & avg sanitation prev.
β	0.9436	0.9587	discount factor

Notes: Model parameters characterizing preferences and discount rate. Column (2) denotes parameter estimates under model with borrowing restricted. Column (3) denotes parameter estimates under no borrowing restrictions. Calibrated values: $r = 0.02$ real interest savings rate based on data from the *Reserve Bank of India* (RBI).

Table 7: First Stage Estimates: Conditional Choice Probability (CCP) Parameters

	Group A (High)		Group B (Low)		Group C (High)		Group D (Low)		
Parameter	**Coeff.**	**Std. Err**	**Coeff.**	**Std. Err**	**Coeff.**	**Std. Err**	**Coeff.**	**Std. Err**	**Description**
$\psi^c_{20\leq a<25}$	0.088	(0.006)	0.032	(0.004)	0.042	(0.004)	0.062	(0.007)	HH head Age $20 \leq a < 25$
$\psi^c_{25\leq a<50}$	0.039	(0.004)	0.021	(0.003)	0.075	(0.008)	0.033	(0.003)	HH head Age $25 \leq a < 50$
$\psi^c_{50\leq a<75}$	-0.022	(0.003)	-0.008	(0.002)	0.001	(0.000)	-0.002	(0.001)	HH head Age $50 \leq a < 75$
ψ^c_{edu}	0.206	(0.013)	0.189	(0.013)	0.244	(0.021)	0.188	(0.018)	HH head Education (yrs)
ψ^c_{asset}	0.071	(0.022)	0.062	(0.014)	0.083	(0.018)	0.058	(0.013)	HH Savings (1000 Rs.)
ψ^c_{inc}	0.331	(0.045)	0.253	(0.042)	0.213	(0.036)	0.268	(0.038)	HH Income (1000 Rs.)
ψ^c_{size}	0.021	(0.004)	0.036	(0.010)	0.041	(0.012)	0.042	(0.010)	Family Size (Nr. Of HH members)
ψ^c_{price}	-0.109	(0.019)	-0.098	(0.010)	-0.116	(0.011)	-0.131	(0.009)	Cost of Sanitation (1000 Rs.)
$\psi^c_{coverage}$	3.811	(0.312)	2.673	(0.264)	3.433	(0.369)	2.851	(0.289)	Sanitation coverage/prevalence
$\psi^c_{\overline{age}}$	0.013	(0.003)	0.021	(0.004)	0.028	(0.003)	0.018	(0.003)	Mean(-i) Age
$\psi^c_{\overline{age}^2}$	-0.001	(0.001)	-0.001	(0.000)	-0.002	(0.001)	-0.002	(0.002)	Mean(-i) Age Sq
$\psi^c_{\overline{edu}}$	0.106	(0.029)	0.181	(0.042)	0.080	(0.018)	0.041	(0.011)	Mean(-i) Education (yrs)
$\psi^c_{\overline{A+y}}$	0.080	(0.012)	0.065	(0.008)	0.101	(0.013)	0.061	(0.010)	Mean(-i) Cash-in-Hand (1000 Rs.)
$\psi^c_{\overline{A+y}^2}$	0.008	(0.002)	0.010	(0.003)	0.011	(0.003)	0.004	(0.001)	Mean(-i) Cash-in-Hand Sq. (1000 Rs.)
ψ^c_0	-3.863	(0.324)	-4.623	(0.481)	-3.920	(0.345)	-4.564	(0.369)	Constant
Drainage Infrastructure	Yes		No		Yes		No		Drainage Infrastructure in village
Community Sanitation	No		Yes		No		Yes		Public sanitation facility in village
Nr. of village in subgroup	9		12		10		11		
Prob. of Adotion (mean)	0.724		0.326		0.867		0.247		

Notes: Parameter Estimates for the conditional choice probabilities by village subgroups. Bootstrapped standard errors in parentheses.

Table 8: Structural Estimates: Village "Fixed Effects"

Village	Data		Coeff. $\widehat{\mu}_g$	Std. Err
	S1	S2		
(mean)			2.24	(0.03)
vill ID 9	0.00	0.00	1.56	(0.07)
vill ID 15	0.00	0.00	1.24	(0.04)
vill ID 18	0.00	0.09	1.42	(0.01)
vill ID 22	0.00	0.13	0.98	(0.05)
vill ID 12	0.00	0.28	0.33	(0.01)
vill ID 19	0.00	0.31	2.12	(0.02)
vill ID 2	0.00	0.42	1.19	(0.02)
vill ID 35	0.06	0.54	0.96	(0.03)
vill ID 40	0.08	0.19	0.67	(0.01)
vill ID 24	0.12	0.35	1.62	(0.02)
vill ID 3	0.14	0.57	0.88	(0.01)
vill ID 37	0.15	0.53	0.45	(0.01)
vill ID 5	0.19	0.26	1.43	(0.03)
vill ID 21	0.19	0.46	1.45	(0.04)
vill ID 11	0.20	0.60	1.69	(0.01)
vill ID 8	0.21	0.50	2.23	(0.05)
vill ID 7	0.25	0.50	1.97	(0.01)
vill ID 4	0.27	0.63	2.35	(0.01)
vill ID 44	0.31	0.47	3.23	(0.04)
vill ID 25	0.33	1.00	2.31	(0.05)
vill ID 6	0.37	0.63	1.41	(0.01)
vill ID 28	0.38	0.38	2.49	(0.02)
vill ID 17	0.45	0.59	2.69	(0.04)
vill ID 14	0.47	0.78	3.91	(0.04)
vill ID 32	0.47	0.89	1.3	(0.03)
vill ID 31	0.50	0.67	2.48	(0.01)
vill ID 27	0.50	0.75	1.86	(0.01)
vill ID 38	0.50	0.86	3.84	(0.08)
vill ID 26	0.61	0.85	4.21	(0.04)
vill ID 20	0.63	0.75	3.64	(0.08)
vill ID 30	0.63	0.79	2.13	(0.02)
vill ID 43	0.67	0.83	0.97	(0.05)
vill ID 29	0.67	0.93	4.12	(0.03)
vill ID 13	0.71	0.94	4.67	(0.04)
vill ID 23	0.71	0.86	3.96	(0.04)
vill ID 36	0.78	0.89	2.34	(0.02)
vill ID 1	0.82	0.90	1.49	(0.05)
vill ID 42	0.82	0.89	2.67	(0.02)
vill ID 39	0.88	0.88	2.57	(0.03)
vill ID 34	0.88	0.96	4.96	(0.02)
vill ID 33	0.88	0.95	3.51	(0.04)
vill ID 16	0.91	1.00	2.88	(0.01)

Notes: Parameter estimates for location (mean) of taste shocks ε_i^d. The villages are listed in increasing order of sanitation coverage. Data:S1 and Data:S2 denote sanitation coverage over the two sample periods. Bootstrapped standard errors in parentheses.

Table 9: Village: Price & Coverage variation

Village	Cost of Sanitation per unit (Rs.)	Data S1	Data S2
vill ID 9	9,725	0.00	0.00
vill ID 15	10,243	0.00	0.00
vill ID 18	10,975	0.00	0.09
vill ID 22	10,016	0.00	0.13
vill ID 12	9,823	0.00	0.28
vill ID 19	10,427	0.00	0.31
vill ID 2	11,337	0.00	0.42
vill ID 35	10,280	0.06	0.54
vill ID 40	10,273	0.08	0.19
vill ID 24	9,510	0.12	0.35
vill ID 3	7,800	0.14	0.57
vill ID 37	9,788	0.15	0.53
vill ID 5	9,801	0.19	0.26
vill ID 21	10,475	0.19	0.46
vill ID 11	10,055	0.20	0.60
vill ID 8	7,938	0.21	0.50
vill ID 7	7,738	0.25	0.50
vill ID 4	8,795	0.27	0.63
vill ID 44	9,913	0.31	0.47
vill ID 25	11,175	0.33	1.00
vill ID 6	8,313	0.37	0.63
vill ID 28	8,131	0.38	0.38
vill ID 17	7,915	0.45	0.59
vill ID 14	8,882	0.47	0.78
vill ID 32	7,155	0.47	0.89
vill ID 31	6,900	0.50	0.67
vill ID 27	8,181	0.50	0.75
vill ID 38	6,775	0.50	0.86
vill ID 26	6,030	0.61	0.85
vill ID 20	8,113	0.63	0.75
vill ID 30	6,662	0.63	0.79
vill ID 43	6,113	0.67	0.83
vill ID 29	7,844	0.67	0.93
vill ID 13	9,924	0.71	0.94
vill ID 23	8,875	0.71	0.86
vill ID 36	6,113	0.78	0.89
vill ID 1	5,713	0.82	0.90
vill ID 42	9,012	0.82	0.89
vill ID 39	6,350	0.88	0.88
vill ID 34	7,963	0.88	0.96
vill ID 33	7,168	0.88	0.95
vill ID 16	11,425	0.91	1.00

Table 10: VILLAGE: SIMULATION BOUNDS

	Data		Mod: $\phi = 0$	Mod: $\phi > 0$
Village	**S1**	**S2**	**LB-UB**	**LB-UB**
vill ID 9	0.00	0.00	(0.00,0.19)	(0.02,0.20)
vill ID 15	0.00	0.00	(0.00,0.25)	(0.00,0.25)
vill ID 18	0.00	0.09	(0.02,0.29)	(0.03,0.29)
vill ID 22	0.00	0.13	(0.10,0.65)	(0.10,0.66)
vill ID 12	0.00	0.28	(0.05,0.29)	(0.05,0.31)
vill ID 19	0.00	0.31	(0.00,0.34)	(0.02,0.35)
vill ID 2	0.00	0.42	(0.05,0.36)	(0.07,0.39)
vill ID 35	0.06	0.54	(0.35,0.68)	(0.36,0.71)
vill ID 40	0.08	0.19	(0.12,0.66)	(0.15,0.68)
vill ID 24	0.12	0.35	(0.18,0.71)	(0.21,0.76)
vill ID 3	0.14	0.57	(0.20,0.76)	(0.26,0.77)
vill ID 37	0.15	0.53	(0.32,0.72)	(0.34,0.78)
vill ID 5	0.19	0.26	(0.19,0.71)	(0.21,0.74)
vill ID 21	0.19	0.46	(0.23,0.63)	(0.61,0.82)
vill ID 11	0.20	0.60	(0.26,0.75)	(0.29,0.76)
vill ID 8	0.21	0.50	(0.24,0.81)	(0.24,0.82)
vill ID 7	0.25	0.50	(0.30,0.82)	(0.32,0.81)
vill ID 4	0.27	0.63	(0.28,0.80)	(0.31,0.85)
vill ID 44	0.31	0.47	(0.33,0.64)	(0.33,0.67)
vill ID 25	0.33	1.00	(0.40, 0.72)	(0.41,0.73)
vill ID 6	0.37	0.63	(0.37,0.78)	(0.37,0.79)
vill ID 28	0.38	0.38	(0.38,0.72)	(0.39,0.75)
vill ID 17	0.45	0.59	(0.56,0.89)	(0.58,0.90)
vill ID 14	0.47	0.78	(0.47,0.82)	(0.75,0.83)
vill ID 32	0.47	0.89	(0.58,0.92)	(0.58,0.93)
vill ID 31	0.50	0.67	(0.62,0.89)	(0.64,0.90)
vill ID 27	0.50	0.75	(0.68,0.83)	(0.68,0.84)
vill ID 38	0.50	0.86	(0.76,0.94)	(0.76,0.94)
vill ID 26	0.61	0.85	(0.72,0.92)	(0.76,0.93)
vill ID 20	0.63	0.75	(0.72,0.93)	(0.72,0.95)
vill ID 30	0.63	0.79	(0.74,0.90)	(0.76,0.94)
vill ID 43	0.67	0.83	(0.78,0.93)	(0.79,0.96)
vill ID 29	0.67	0.93	(0.73,0.95)	(0.73,0.99)
vill ID 13	0.71	0.94	(0.78,0.97)	(0.81,1.00)
vill ID 23	0.71	0.86	(0.81,0.98)	(0.81,0.99)
vill ID 36	0.78	0.89	(0.81,0.96)	(0.81,0.97)
vill ID 1	0.82	0.90	(0.83,0.97)	(0.86,0.98)
vill ID 42	0.82	0.89	(0.83,0.94)	(0.83,0.94)
vill ID 39	0.88	0.88	(0.89,0.99)	(0.89,1.00)
vill ID 34	0.88	0.96	(0.88,0.98)	(0.89,1.00)
vill ID 33	0.88	0.95	(0.88,0.99)	(0.88,1.00)
vill ID 16	0.91	1.00	(0.91,0.98)	(0.95,0.99)

Table 11: Simulation Bounds (Perturbation ϕ)

	Data			Mod: $\phi = 0$					Mod: $\widehat{\phi} = 0.00514$
Village	**S1**	**S2**		**P1**	**P2**	**P3**	**P4**	**P5**	**P6**
vill ID 24	0.120	0.350	**LB**	0.181	0.185	0.190	0.194	0.197	0.208
			UB	0.712	0.727	0.733	0.744	0.751	0.758
vill ID 3	0.140	0.570	**LB**	0.201	0.206	0.222	0.237	0.258	0.263
			UB	0.764	0.765	0.765	0.767	0.769	0.770
vill ID 21	0.190	0.460	**LB**	0.230	0.272	0.357	0.484	0.590	0.611
			UB	0.626	0.691	0.734	0.798	0.820	0.820
vill ID 14	0.470	0.780	**LB**	0.470	0.549	0.581	0.628	0.675	0.754
			UB	0.817	0.818	0.820	0.821	0.823	0.827
vill ID 13	0.710	0.940	**LB**	0.776	0.781	0.787	0.790	0.799	0.808
			UB	0.973	0.976	0.984	0.991	0.999	1.000

Table 12: Village: Social Planner Problem

Village	Total #HH (approx)	Total Endowment value (x1000 Rs.)	Cost of Sanitation per unit (x1000 Rs.)	Data S1	Utilitarian Social Planner	Under-adoption (%)
vill ID 9	190	8,217.88	9.725	0.00	0.72	100%
vill ID 15	162	8,201.25	10.243	0.00	0.73	100%
vill ID 18	301	12,474.04	10.975	0.00	0.78	100%
vill ID 22	240	10,410.00	10.016	0.00	0.75	100%
vill ID 12	121	4,154.29	9.823	0.00	0.74	100%
vill ID 19	210	5,995.29	10.427	0.00	0.73	100%
vill ID 2	470	23,028.12	11.337	0.00	0.77	100%
vill ID 35	762	31,341.06	10.280	0.06	0.62	91%
vill ID 40	360	22,363.56	10.273	0.08	0.74	89%
vill ID 24	873	42,891.36	9.510	0.12	0.66	82%
vill ID 3	786	28,177.31	7.800	0.14	0.58	77%
vill ID 37	306	10,324.13	9.788	0.15	0.70	79%
vill ID 5	270	13,786.47	9.801	0.19	0.76	76%
vill ID 21	282	18,634.28	10.475	0.19	0.81	77%
vill ID 11	100	4,572.00	10.055	0.20	0.72	72%
vill ID 8	308	19,836.43	7.938	0.21	0.82	74%
vill ID 7	226	9,754.84	7.738	0.25	0.78	68%
vill ID 4	633	56,674.39	8.795	0.27	0.92	70%
vill ID 44	313	27,611.92	9.913	0.31	0.89	65%
vill ID 25	109	4,756.76	11.175	0.33	0.78	57%
vill ID 6	200	12,018.20	8.313	0.37	0.77	52%
vill ID 28	164	19,903.53	8.131	0.38	0.94	60%
vill ID 17	324	15,900.95	7.915	0.45	0.84	46%
vill ID 14	220	10,798.04	8.882	0.47	0.75	38%
vill ID 32	187	12,615.58	7.155	0.47	0.76	38%
vill ID 31	127	8,930.64	6.900	0.50	0.74	32%
vill ID 27	120	4,304.76	8.181	0.50	0.74	32%
vill ID 38	328	28,304.10	6.775	0.50	0.91	45%
vill ID 26	413	22,870.29	6.030	0.61	0.88	31%
vill ID 20	169	10,431.53	8.113	0.63	0.87	28%
vill ID 30	366	23,321.89	6.662	0.63	0.86	26%
vill ID 43	140	13,040.02	6.113	0.67	0.91	27%
vill ID 29	453	27,705.03	7.844	0.67	0.88	24%
vill ID 13	340	16,649.12	9.924	0.71	0.96	26%
vill ID 23	168	11,790.41	8.875	0.71	0.91	22%
vill ID 36	280	22,333.92	6.113	0.78	0.94	17%
vill ID 1	347	22,793.04	5.713	0.82	0.91	10%
vill ID 42	273	21,557.72	9.012	0.82	0.85	3%
vill ID 39	163	8,761.58	6.350	0.88	0.78	-12%
vill ID 34	215	11,279.98	7.963	0.88	0.89	2%
vill ID 33	314	20,301.04	7.168	0.88	0.91	3%
vill ID 16	167	12,332.95	11.425	0.91	0.92	1%

Notes: This table show the socially optimal level of sanitation coverage Social Planner calculations are performed using endowment level from observed villages in period $S1$. Column (5) and (6) denote the proportion of sanitation adoption observed in the data and under the social planner solution respectively. On average the extent of under-adoption of sanitation is close to 53% with respect to a utilitarian SWF, where the planner assigns equal pareto weights to each household in the village. £1 $\approx$ $Rs.\,100\,(INR)$.

Table 13: Village: Price Subsidy Simulated Bounds

Village	Cost of Sanitation (Rs.)	Data S1	Pol: Price Subsidy (LB-UB)			
			No Subsidy	Sub: 5%	Sub: 15%	Sub: 25%
vill ID 9	9,725	0.00	(0.02,0.20)	(0.05,0.25)	(0.18,0.72)	(0.64,0.98)
vill ID 15	10,243	0.00	(0.00,0.25)	(0.02,0.26)	(0.12,0.42)	(0.72,0.88)
vill ID 18	10,975	0.00	(0.03,0.29)	(0.05,0.30)	(0.15,0.48)	(0.65,0.80)
vill ID 22	10,016	0.00	(0.10,0.66)	(0.10,0.66)	(0.17,0.67)	(0.81,0.90)
vill ID 12	9,823	0.00	(0.05,0.31)	(0.05,0.31)	(0.23,0.62)	(0.84,0.91)
vill ID 19	10,427	0.00	(0.02,0.35)	(0.03,0.35)	(0.08,0.41)	(0.68,0.75)
vill ID 2	11,337	0.00	(0.07,0.39)	(0.09,0.39)	(0.12,0.43)	(0.62,0.88)
vill ID 35	10,280	0.06	(0.36,0.71)	(0.38,0.71)	(0.65,0.84)	(0.72,0.91)
vill ID 40	10,273	0.08	(0.15,0.68)	(0.17,0.69)	(0.19,0.72)	(0.59,0.78)
vill ID 24	9,510	0.12	(0.21,0.76)	(0.28,0.79)	(0.31,0.83)	(0.66,0.90)
vill ID 3	7,800	0.14	(0.26,0.77)	(0.35,0.79)	(0.84,0.96)	(0.91,0.99)
vill ID 37	9,788	0.15	(0.34,0.78)	(0.36,0.79)	(0.71,0.86)	(0.76,0.92)
vill ID 5	9,801	0.19	(0.21,0.74)	(0.30,0.78)	(0.64,0.82)	(0.70,0.86)
vill ID 21	10,475	0.19	(0.61,0.82)	(0.62,0.84)	(0.66,0.89)	(0.69,0.90)
vill ID 11	10,055	0.20	(0.29,0.76)	(0.29,0.78)	(0.32,0.79)	(0.62,0.84)
vill ID 8	7,938	0.21	(0.24,0.82)	(0.32,0.83)	(0.63,0.85)	(0.68,0.88)
vill ID 7	7,738	0.25	(0.32,0.81)	(0.34,0.82)	(0.70,0.88)	(0.76,0.93)
vill ID 4	8,795	0.27	(0.31,0.85)	(0.37,0.89)	(0.68,0.92)	(0.75,0.96)
vill ID 44	9,913	0.31	(0.33,0.67)	(0.36,0.69)	(0.76,0.92)	(0.86,0.95)
vill ID 25	11,175	0.33	(0.40, 0.72)	(0.43,0.74)	(0.48,0.76)	(0.62,0.91)
vill ID 6	8,313	0.37	(0.37,0.79)	(0.38,0.79)	(0.61,0.83)	(0.66,0.84)
vill ID 28	8,131	0.38	(0.39,0.75)	(0.41,0.76)	(0.60,0.79)	(0.65,0.82)
vill ID 17	7,915	0.45	(0.58,0.90)	(0.72,0.91)	(0.75,0.92)	(0.78,0.98)
vill ID 14	8,882	0.47	(0.75,0.83)	(0.78,0.84)	(0.80,0.89)	(0.88,0.97)
vill ID 32	7,155	0.47	(0.58,0.93)	(0.70,0.94)	(0.73,0.95)	(0.80,1.00)
vill ID 31	6,900	0.50	(0.64,0.90)	(0.67,0.91)	(0.72,0.94)	(0.81,0.97)
vill ID 27	8,181	0.50	(0.68,0.84)	(0.72,0.85)	(0.81,0.92)	(0.84,0.93)
vill ID 38	6,775	0.50	(0.76,0.94)	(0.78,0.94)	(0.81,0.94)	(0.82,0.95)
vill ID 26	6,030	0.61	(0.76,0.93)	(0.78,0.94)	(0.82,0.96)	(0.88,0.99)
vill ID 20	8,113	0.63	(0.72,0.95)	(0.75,0.96)	(0.79,0.96)	(0.86,0.99)
vill ID 30	6,662	0.63	(0.76,0.94)	(0.80,0.96)	(0.83,0.96)	(0.88,0.97)
vill ID 43	6,113	0.67	(0.79,0.96)	(0.79,0.96)	(0.84,0.97)	(0.88,0.99)
vill ID 29	7,844	0.67	(0.73,0.99)	(0.75,0.99)	(0.78,0.99)	(0.82,1.00)
vill ID 13	9,924	0.71	(0.81,1.00)	(0.84,1.00)	(0.88,1.00)	(0.89,1.00)
vill ID 23	8,875	0.71	(0.81,0.99)	(0.84,1.00)	(0.85,1.00)	(0.88,1.00)
vill ID 36	6,113	0.78	(0.81,0.97)	(0.82,0.97)	(0.86,0.98)	(0.94,0.99)
vill ID 1	5,713	0.82	(0.86,0.98)	(0.87,0.98)	(0.92,0.99)	(0.93,0.99)
vill ID 42	9,012	0.82	(0.83,0.94)	(0.86,0.96)	(0.88,0.96)	(0.92,0.97)
vill ID 39	6,350	0.88	(0.89,1.00)	(0.89,1.00)	(0.90,1.00)	(0.90,1.00)
vill ID 34	7,963	0.88	(0.89,1.00)	(0.91,1.00)	(0.92,1.00)	(0.93,1.00)
vill ID 33	7,168	0.88	(0.88,1.00)	(0.88,1.00)	(0.90,1.00)	(0.90,1.00)
vill ID 16	11,425	0.91	(0.95,0.99)	(0.95,1.00)	(0.95,1.00)	(0.96,1.00)

Notes: Policy simulations are performed on observed villages. £1 $\approx$ $Rs.100\,(INR)$.

Table 14: Simulated Bounds under different policies

Initial Sanitation	Policy Effect: Equilibrium Sanitation (LB-UB)		
Coverage (Fraction)	Uncond Loan	Sanitation Loan (100% of cost)	Price Subsidy (25% of cost)
0	(0.07,0.28)	(0.02,0.39)	(0.16,0.42)
0.05	(0.11,0.35)	(0.05,0.46)	(0.21,0.58)
0.15	(0.28,0.49)	(0.16,0.58)	(0.39,0.66)
0.25	(0.38,0.60)	(0.26,0.69)	(0.47,0.78)
0.35	(0.60,071)	(0.42,0.75)	(0.66,0.81)
0.45	(0.71,0.77)	(0.69,0.84)	(0.75,0.88)
0.55	(0.75,0.81)	(0.81,0.90)	(0.82,0.91)
0.65	(0.82,0.86)	(0.88,0.93)	(0.90,0.96)
0.75	(0.85,0.91)	(0.94,0.98)	(0.96,0.98)
0.85	(0.91,0.96)	(0.95,0.98)	(0.98,0.98)
0.95	(0.95,0.98)	(0.97,0.99)	(0.98,1.00)

Notes: Policy simulations are performed on a counterfactual village where the initial distribution of all state variables: age, assets, income and cost of sanitation $Rs.8628$ excluding the initial sanitation coverage are held constant. The initial sanitation coverage is determined by generating a random allocation of sanitation for different households in the village holding fixed all other characteristics.

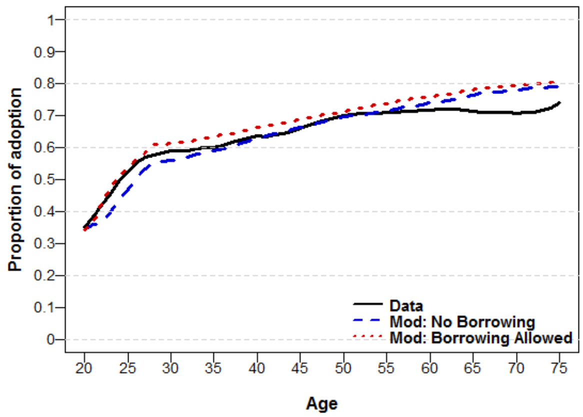
Table 15: Household Valuation of Sanitation

	Compensation Amount (x 1000 Rs.)	
Age	No Ext	With Ext (LB-UB)
20	259.8	(578.4,884.6)
25	242.3	(557.1,834.6)
30	185.3	(483.8,732.4)
35	158.8	(389.6,632.5)
40	140.2	(326.5,561.4)
45	128.4	(259.8,438.5)
50	110.8	(224.0,328.5)
55	89.3	(163.4,267.2)
60	72.3	(125.4,189.2)
65	56.2	(96.4,136.1)
70	33.45	(63.2,97.5)
74	12.6	(35.7,63.5)

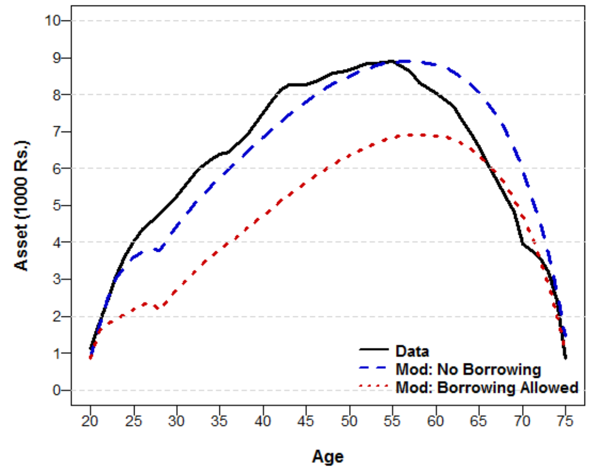
Notes: Compensation amount denotes the valuation of sanitation made by a household. The amounts are computed for a representative household at different ages £1 $\approx$ $Rs.100\,(INR)$.

F Figures

Figure 11: Model Fit: Impact of Liquidity Constraints



(a) Proportion of Sanitation Adoption



(b) Assets over the life cycle (1000 *Rs.*)

Figure 12: Model: Household Income

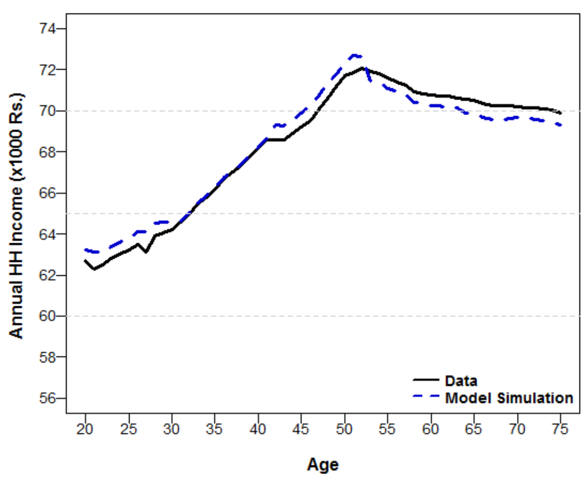
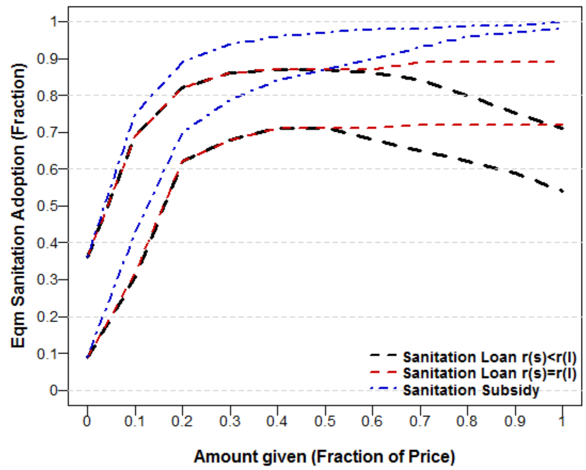
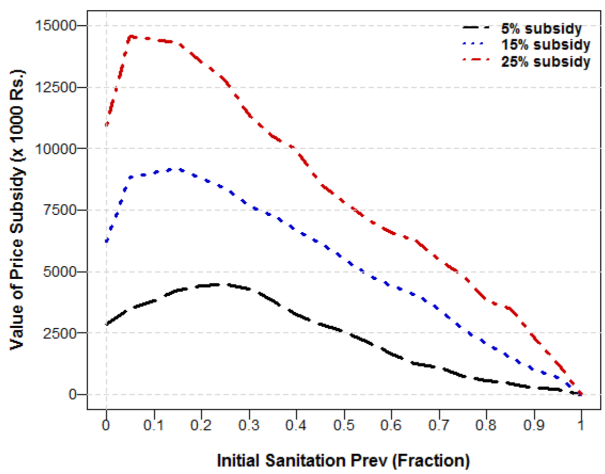


Figure 13: Equilibrium Adoption: Size of Loans & Subsidies



Notes: The simulations plot the upper and lower bound for the predicted equilibrium sanitation level one period ahead. Policy simulations are performed on a counterfactual village where the initial distribution of all state variables: age, assets, income and cost of sanitation $Rs.$ 8628 are held constant and the initial sanitation coverage is fixed at 0%.

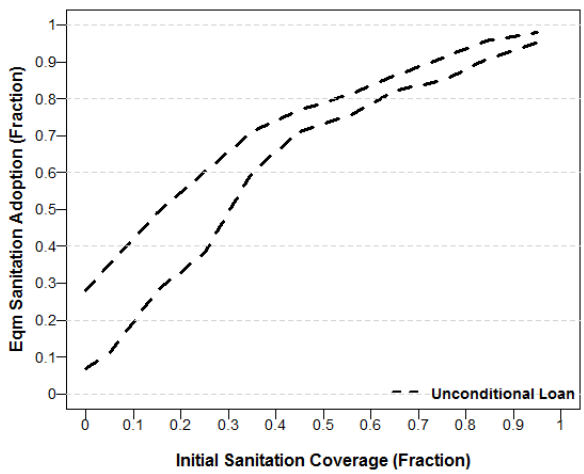
Figure 14: Value of price subsidy: lower bound



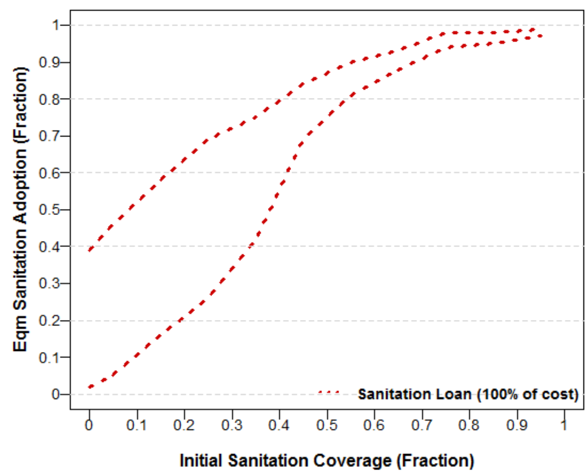
Notes: The simulations plot the lower bound for the value of subsidy one period ahead. Policy simulations are performed on a counterfactual village where the initial distribution of all state variables: age, assets, income and cost of sanitation *Rs.* 8628 excluding the initial sanitation coverage are held constant. The initial sanitation coverage is determined by generating a random allocation of sanitation for different households in the village holding fixed all other characteristics.

Figure 15: Simulated Policy Bounds

(a) Unconditional Loan



(b) Sanitation Loan (100% of cost)



(c) Price subsidy (25% of cost)