Choosing Amongst Health Providers: How Conditional Cash Transfers Affect Long-Term Behavior*

David Glick†

October 14, 2014

Abstract

Demand-side incentives have been shown to increase participation in the formal health care sector in many developing countries. Much attention has been paid to the direct and short-term effects of these financial incentives, but little evidence exists regarding how short-term subsidies may affect long-term behavior. We study how a conditional cash transfer program in India, *Janani Suraksha Yojana* (JSY), which incentivizes women to deliver babies in medical facilities, affects their propensity to seek formal treatment for themselves and their children for future illnesses. We first estimate district-level program start dates using a mean-shift model, and argue that these dates are exogenous to other factors which may also affect facility choice. Using spatial and temporal variation in start dates, we find that JSY increased institutional deliveries by 5.5 percentage points nationwide, but by 11.4 percentage points in states that were given special attention under the program. These gains are limited to the public sector as mothers substitute away from private facilities. Women who utilize public medical facilities for childbirth are also 6.8 percentage points more likely to seek treatment for sick children later in life, but no more likely to seek treatment for themselves when ill. A model of facility choice suggests this effect on future health-seeking behavior is driven both by paying one-time experience costs and through learning about facility quality.

Keywords: Health, Program Implementation and Evaluation, Learning.
JEL Classification: I38, D83, H75.

*I am grateful to Anna Aizer, Ken Chay, Andrew Foster, Nathaniel Hilger, and Sriniketh Nagavarapu for their feedback and guidance. I also thank Benjamin Handel, Ali Hortaçsu, and participants of Brown University's Applied Microeconomics Lunch for their comments. I acknowledge Brown's Population Studies and Training Center for their support in acquiring data for this project, and thank Brown's Economics Department for awarding an earlier draft the Third-Year Paper Prize. Remaining errors and omissions are my own.

†Department of Economics, Box B; Brown University; Providence, RI 02912. david_glick@brown.edu.

1 Introduction

Low utilization of medical facilities is prevalent throughout India. DLHS-III survey data indicates that in 2005, nearly 70 percent of rural women were delivering their babies at home. These utilization rates are in part caused by supply-side factors which limit the accessibility and effectiveness of treatment. Public medical facilities in developing countries are often characterized by weak incentives and widespread absenteeism (Chaudhury and Hammer (2005)), low levels of provider knowledge related to basic care (Das and Hammer (2004)), and providers giving a standard of care that is well below their clinical knowledge (Das *et. al.* (2008); Leonard and Masatu (2010); Gertler and Vermeersch (2013)).

But demand-side factors also limit individuals' use of health facilities, including financial constraints, heavily discounting the future, lack of knowledge about available services, and low expectations of service quality. In light of these facts, financial incentives and subsidies for health products have become a key feature of programs directed at increasing demand for health care (see Gneezy *et. al.* (2011) for a review). Two traditionally used economic rationales for offering subsidies are: first, they relax the budget constraint for poor or credit-constrained households; and second, in the case of health where treatment and disease prevention have positive externalities, private investment in health is socially suboptimal.

A newer strand of literature has explored an additional rationale, namely how short-run subsidies may impact long-term health behavior (Dupas (2014)). If a health product or service is an experience good, a subsidy will allow a first-time consumer to learn about the characteristics of that product or service, affecting her future demand. On the other hand, if information asymmetries are low, financial incentives may have little long-term effect. Further, if individuals experience an entitlement effect from a subsidy where they become price reference-dependent, short-run incentives may in fact dampen future care-seeking behavior. Little empirical evidence exists, however, as to which of these effects dominates.

This paper sheds light on how a one-time cash transfer affects future health-seeking behavior in India. We analyze the effects of a nationally-sponsored program, *Janani Suraksha Yojana* (JSY), on mothers' choice of health facilities in India. Under JSY eligible mothers can receive a cash transfer for delivering their newborn children in a public medical facility or an accredited private health center. For some women using a health facility for childbirth may be their first experience with the formal health care sector. We explore whether institutional delivery (delivery in a formal health facility as opposed to at home), induced by JSY, increases the probability that women utilize the formal health care sector again later in their lives.

Women choose health providers based on many observable factors, including price and location. But choices are also made based on unobserved traits such as preferences for public vs. private entities and expectations about future need for medical care. In the case of childbirth, institutional delivery may be favorably selected if these births are positively correlated with income and maternal education. Conversely, medical facility births may be adversely selected if women who anticipate a difficult delivery are more likely to choose hospital over home delivery. Self-selection into health facility alternatives thus makes estimating the effects of past facility choice on future choice difficult. We address this selection concern by exploiting variation in JSY's eligibility rules and the timing of its adoption across India.

More than 300,000 Indian newborns die yearly on the day of their birth, accounting for 29.5 percent of all global birthday deaths. Infections and birth complications are responsible for 46 percent of these, many of which could be prevented by a health worker with the right skills, equipment, or support. Further, the lifetime risk of maternal mortality for Indian women is one in 170 (Save the Children (2013)). With these relatively poor indicators, coupled with high rates of home births, the Indian Government launched JSY with the hopes of improving infant and maternal health. From its inception in April 2005 through July 2014, more than 73 million births were supported under JSY. While previous work has explored the effects of institutional births on health outcomes (Powell-Jackson and Hanson (2012) in Nepal; Okeke and Chari (2013) in Rwanda), we focus on whether JSY leads to persistence in health facility-seeking behavior.

There are many mechanisms through which a subsidy for formal medical care may affect future behavior. First, there may be a pure income effect since medical care is costly and the subsidy relaxes the household's budget constraint. Second, if individuals purchase a product or service many times at a subsidized price, they may perceive a later unsubsidized price as a negative price shock and cease consumption. Alternatively, continued use of a health service may result in habit formation and persistent use of that service even when incentives end. Third, a subsidy which induces use of formal medical care may allow individuals to learn about service quality, thereby revising their expectations over future quality of care. Learning can occur at the individual level, though information may also diffuse through social networks (Aizer and Currie (2004); Leonard (2007) and (2009)), and is likely to be a particularly relevant channel in the context of India where quality of care varies widely across facilities (Das *et. al.* (2013)). Fourth, there are non-monetary experience costs to utilizing a medical facility for the first time. These include figuring out its exact location and modes of transportation, learning about the administrative and bureaucratic procedures of registering and paying for services, and filling out medical record forms or taking the time to explain one's medical history to a doctor. Many of these may only need to be done once, making future use of the same facility easier and faster. Many Indian health workers are present and outpatient departments are open only on certain days (Chaudhury *et. al.* (2004); Roy *et. al.* (2013)), and wait times for women to be served by medical personal for outpatient care for themselves or their child average 45.3 and 35.5 minutes in public and private facilities, respectively (DHS 2005-06). Thus utilizing a facility may help inform women which are the best days and times to go in the future. If a subsidy induces an individual to use a facility, pay these experience costs thereby gaining knowledge about the process, she may be more likely to use that facility again since these costs will not need to be paid anew.

From a policy perspective, understanding how individuals make choices about health care is important. If learning about quality occurs with respect to medical treatment in India, or if people internalize having paid an experience cost, financial incentives which encourage short-term use of the formal health sector may have important long-term impacts on individuals' health as well as the market for health care.

A small literature has emerged which explores the effect of incentive programs on changing health behaviors in the United States (Volpp *et. al.* (2008); Charness and Gneezy (2009); Babcock and Hartman (2011)). Overall it points to strong responses to financial incentives, but studies also typically find disappointing long-term results where individuals revert back to old patterns of behavior once incentives end. Some exceptions in the developing world include Dupas (2014), who finds that temporary subsidies increase willingness to pay for bed nets through learning in Kenya, and Barham *et. al.* (2012), who find utilization of preventive care in Nicaragua to be higher for households that received a cash transfer even after payment ended. Studies about JSY have focused primarily on health outcomes for newborns. Debnath (2013) finds that JSY increased institutional delivery by nine percentage points, increased utilization of pre- and post-natal care, and increased newborn immunizations using a difference-in-difference strategy comparing outcomes before and after April 2005. Mazumdar *et. al.* (2011) and Dongre (2012) also find positive effects of JSY on institutional delivery, as well as note small amounts of substitution away from private health providers and towards public ones. Mazumdar *et. al.* (2011) employs an instrumental variables design by estimating a program start date for each district, but does so by choosing an arbitrary threshold for the percent of mothers receiving the cash transfer above which they assume the program started. Lastly, Lim *et. al.* (2010) find substantial district- and state-level variation in changes in institutional delivery rates after the program's implementation.

This paper deviates from these previous studies in four distinct ways. First, the aforementioned studies on the long-term impacts of incentive programs examine situations where individuals are faced with the same choice scenario both during and after the incentive program. For example, the choice scenario of whether or not to go to the gym (Charness and Gneezy (2009)) or purchase a bed net (Dupas (2014)) is constant over time. We, however, examine how incentives for one action affect post-incentive decisions for different, but complementary actions; namely, incentives for institutional delivery, but future choices to seek treatment in the formal health care sector for other medical needs. This paper therefore expands upon the existing literature by analyzing how financial incentives for one action may impact long-term complementary behavior.

Second, instead of choosing an arbitrary threshold to decide on district-level JSY start dates, we formally estimate the month JSY started in each district using a mean-shift model. This method comes from the literature on estimating structural breaks, and thus we show the usefulness of this methodology in the context of program evaluation. The Central Government initiated JSY with a highly decentralized framework, whereby districts would operationalize the program at the local level. We hypothesize that India's nearly 600 districts at the time did not all launch JSY concurrently, and find that districts on average took 23.1 months to implement the program. We then exploit this cross sectional and temporal variation in program implementation to analyze JSY's impact on use of medical facilities. One methodological concern with using variation in district-level start dates to identify medical facility choice is that that local governments dictate the timing of program implementation, and this timing may not be orthogonal to characteristics of districts which also influence mothers' choice of medical facilities. We address this concern in two ways, including using a hazard model of program adoption that allows for duration dependence to analyze how start dates are correlated with factors that may affect both implementation and facility choice.

Third, unlike some previous studies we take into account changes in program incentives and eligibility that occurred in late 2006. Cash incentives increased and eligibility was expanded after November 2006, thus we explore whether these expansions led to differential impacts between the early and late phases of the program. Ignoring these program changes leads to bias in selecting district-level start dates as well as bias in the interpretation of the mechanisms which induce take-up of institutional delivery. We find that JSY increased institutional deliveries overall by 5.5 percentage points, but by 11.4 percentage points in states that were designated as "low performing" prior to JSY. In these states an additional 4.9 percent of women substituted away from private facilities and towards public ones. Eligible women are 3.0 percentage points more likely to utilize a medical facility in the later program period relative to the early period, suggesting that households respond both to the transfer's extensive and intensive margins.

Fourth, whereas the previous literature primarily focuses on the direct health benefits of JSY, this paper expands on the program effects by examining whether delivering in a medical facility affects the tendency of women to utilize medical facilities for non-birth related needs in the future. We find that women who deliver in public medical facilities, instrumented by the existence of JSY at the time of childbirth, are 6.8 percentage points more likely to seek treatment for their sick children relative to those who did not deliver in public institutions.

Women are not, however, more likely to seek treatment for themselves when facing medical problems later in life. We develop a simple theoretical model of facility choice in order to better understand the mechanisms that may be driving this result. Empirically testing the model's predictions, we provide suggestive evidence that this positive effect of institutional delivery on future treatment is driven both by paying one-time experience costs and though learning about facility quality. Income effects, however, are unable to explain these findings.

The remainder of this paper is organized as follows: Section 2 discusses the institutional setting of JSY; Section 3 details the data used in subsequent analysis; Section 4 outlines a theoretical model of facility choice; Section 5 details the empirical strategy and includes a discussion of the estimation of district-level JSY start dates; Section 6 reports on the effects of JSY on facility choice and utilization; Section 7 concludes; and Section 8 is an Appendix.

2 Institutional Setting of *Janani Suraksha Yojana*

In order to ensure maternal and infant health for poor households, the Central Government launched the National Maternity Benefit Scheme (NMBS) in August 1995. The NMBS provided an unconditional cash transfer of Rs. 500 per birth to below poverty line (BPL) households for pre- and post-natal care. This payment was irrespective of whether a mother delivered her child at home or in a medical facility.

In April 2005 India's Central Government initiated *Janani Suraksha Yojana*, or Safe Motherhood Scheme, as part of a larger National Rural Health Mission (NRHM). JSY is a conditional cash transfer program with the objective of reducing maternal and neonatal mortality by promoting institutional delivery. All states and Union Territories were required to adopt the program, but 10 states were deemed to be "low performing states" while the remaining 18 states were classified as "high performing states."[1] Financial incentives vary across state types. The condition for receiving JSY funds was receiving pre-natal care as well as delivering in a public medical facility or accredited private institution. JSY was meant to replace the NMBS, meaning that a mother could now only receive a cash transfer by utilizing institutional delivery. In practice, however, the NMBS continued to function in some states.

In addition to JSY's demand-side incentives, supply-side changes were also initiated by the program. JSY mobilized existing Accredited Social Health Activists (ASHAs), community-level health workers, to identify pregnant women for institutional delivery and travel with them to a facility for delivery. ASHA workers were trained in basic health care practices, and

[1]Low states include Assam, Bihar, Chhattisgarh, Jammu and Kashmir, Jharkhand, Madhya Pradesh, Orissa, Rajasthan, Uttar Pradesh, and Uttrakhand. High states include Andhra Pradesh, Arunachal Pradesh, Goa, Gujarat, Haryana, Himanchal Pradesh, Karnataka, Kerala, Maharashtra, Manipur, Meghalaya, Mizoram, Nagaland, Punjab, Sikkim, Tamil Nadu, Tripura and West Bengal. A state-wide institutional delivery rate of less than 25 percent was the Center's main criteria for selecting states as low performing.

received performance based incentives for promoting pre- and post-natal care, institutional delivery, and immunizations of newborns.

2.1 Eligibility and Cash Incentives

Eligibility and cash incentives vary both by state type and region. Initially, in both low and high states, eligibility was restricted to women at least 19 years old and who were from BPL households. However, due to low take-up of the program in its initial years, eligibility was expanded in November 2006. Thereafter, all women in low states, regardless of age or BPL status, could receive the transfer if delivering in a government-run facility. Additionally, in low states women of any age from BPL households, and women from scheduled castes or tribes, could receive the transfer if delivering in an accredited private facility. In high states the age requirement was maintained, but women from scheduled castes and tribes (who were not BPL) could also avail the benefit.[2]

Table 1 details the cash incentives to mothers and ASHA workers by state type, region, and time. Starting in April 2005 mothers could receive Rs. 700 for institutional delivery in rural areas, and in low states Rs. 600 for delivery in urban areas. In November 2006 incentives increased to Rs. 1,400 and 1,000 in low states for rural and urban areas, respectively, and a Rs. 600 incentive was added for urban areas of high states. To put these figures into context, average per capita monthly expenditures across India in 2004-05 were Rs. 579 and 1,104 in rural and urban areas, respectively.[3] Thus the JSY incentives are sizable. Based on the incentive structure and changes over time we would expect JSY to be more effective: a) in rural relative to urban areas (both because of the nominal value of the incentives and differences in relative price levels); b) in low relative to high states; and c) after November 2006. Payment to mothers are to be made at the institution at the time of delivery, while ASHA workers are to receive two installments (one after registering the expectant mother and a second after a post-natal visit). In practice, however, delays in payments are common.

3 Data

We rely primarily on household-level data from the third round of the District Level Household and Facility Survey, DLHS-III (2007-08). The DLHS, executed by the Indian Institute of Population Sciences, is one of the largest demographic health surveys in India. The Ministry of Health and Family Welfare, Government of India, first initiated the DLHS in 1997 to provide district-level estimates on health indicators and to assist policymakers in planning,

[2] Until 2013 eligibility was restricted to two live births per woman so as not to encourage higher fertility.

[3] Planning Commission, Government of India,"State-wise Indicators of Poverty and Per-capita Expenditure." Conversion rate: \$1 USD $\approx$ Rs. 60 in July 2014.

Table 1:
Cash Incentives Under JSY (in Rupees)

		Low Performing States		High Performing States	
Effective Date[1]	Recipient	Rural	Urban	Rural	Urban
April 2005	Mother	700	600	700	-
	ASHA	600	200	-	-
November 2006	Mother	1,400	1,000	700	600
	ASHA	600	200	200	200

[1] Incentives changed again after 2008, but this is beyond the time frame of this study.

monitoring, and evaluation. The DLHS-III is designed to provide estimates on maternal and child health, family planning and other reproductive health services, as well as information related to the programs of the NRHM. The DLHS-III interviewed 720,320 households (900 to 1,650 households from each of 601 districts) between late 2007 and late 2008. Concurrent with the household surveys, the DLHS-III conducted village level surveys on the availability and accessibility of various facilities in rural villages, especially regarding health facilities. A facilities survey was also carried out to collect information on the availability and quality of government health care institutions. We also employ the DLHS-II (2003) facility survey which took place in 370 districts to examine changes in public facility quality over time.

To analyze the timing of JSY's implementation across India we also utilize data from the Election Commission of India which details the political party affiliation and gender of Members of states' Legislative Assemblies (MLAs). In the relevant period (2005-2006) there were 3,960 constituencies (each with its own MLA) in the 27 states in which we focus. We are able to match 3,887 (98.2 percent) of these constituencies to their respective districts, leaving us with detailed MLA information for 563 districts (96.9 percent of all districts) in these 27 states.[4] We use Census of India data from 2001 and 2011, and calculate annual populations using a linear extrapolation between census years. We draw upon the 2005-06 Indian Demographic and Health Survey for data on outpatient wait times, and adjust prices using monthly inflation rates from the Ministry of Statistics and Programme Implementation.

3.1 Estimation Sample and Summary Statistics

The DLHS-III asks retrospectively about all births from January 2004 through the time of interview for ever-married women (ages 15-49). Most delivery related questions are asked only for the most recent birth so our primary sample has only one birth per woman. We

[4]We thank Sandip Sukhtankar and Manasa Patnam for making available Indian Assembly Constituency shapefiles that correct errors in the data provided by the Election Commission of India.

restrict our sample to women living in 581 districts from 27 states who had a live or still birth, leaving us with 216,479 unique births from 204,576 households over a five year period.[5]

Table 2 shows summary statistics by state type for household and delivery characteristics for women that gave birth during the sample frame. Households in high states are more urban and educated relative to those in low states. Median distances to all types of government and private health centers are similar across state types. Across all states only 3.4 percent of households have health insurance of any kind.

By design, more than twice as many women in low states are eligible for the JSY transfer. Prior to JSY's introduction in April 2005, only 25.2 percent of women in low states utilized institutional delivery (both public and private combined) compared with 59.9 percent in high states. During the period from April 2005 through the end of 2008, these figures changed to 33.0 and 59.8 percent in low and high states, respectively. Transportation costs to medical facilities are higher in low states, likely due to households living in more rural locations. Payment for services are considerably lower at public facilities across both state types. While medical care at government facilities is supposed to be free, or at most require nominal fees for some services, in practice patients are forced to make payments to different personnel for medicine, supplies, or use of a room. Comparing mean prices for home deliveries to mean costs at government facilities plus transportation fees, delivery at public locations costs approximately Rs. 1,000 more across all state types. If costs are the main criteria households use to select delivery location, these facts, coupled with the size of the JSY transfer, imply that JSY would not induce everyone to utilize institutional delivery.

We also examine trends in delivery locations before and after JSY's implementation. Figure 1 depicts delivery rates by state type and urban/rural regions. Vertical lines are placed at two dates: first, when JSY was officially announced in April 2005; and second, when eligibility and incentives changed in November 2006. Before April 2005 institutional delivery rates were constant in all panels. During the first phase of JSY there is no evident change in locations in urban areas or high states, whereas there is a small increase in institutional delivery in rural areas of low states. This is not surprising given the incentives outlined in Table 1. After late 2006, however, there is a sharp rise in institutional deliveries in rural and urban areas of low states. We also depict trends in delivery locations by eligibility for the JSY transfer. Again rates are constant in Figure 2 for the period before initial implementation in all four panels.[6] Institutional delivery rates increase slightly for early eligibles in the initial program period, but the increase is much more pronounced after late 2006.

[5]We exclude India's Union Territories due to their small size and lack of information on NRHM programs in these areas, and only one state (Nagaland) since it was not surveyed in the DLHS-III.

[6]We omit a panel for late eligibles in high states due to very few observations. In low states there are no women that are never eligible.

Figure 1:
Deliveries by Location and Region

Figure 2:
Deliveries by Location and Eligibility

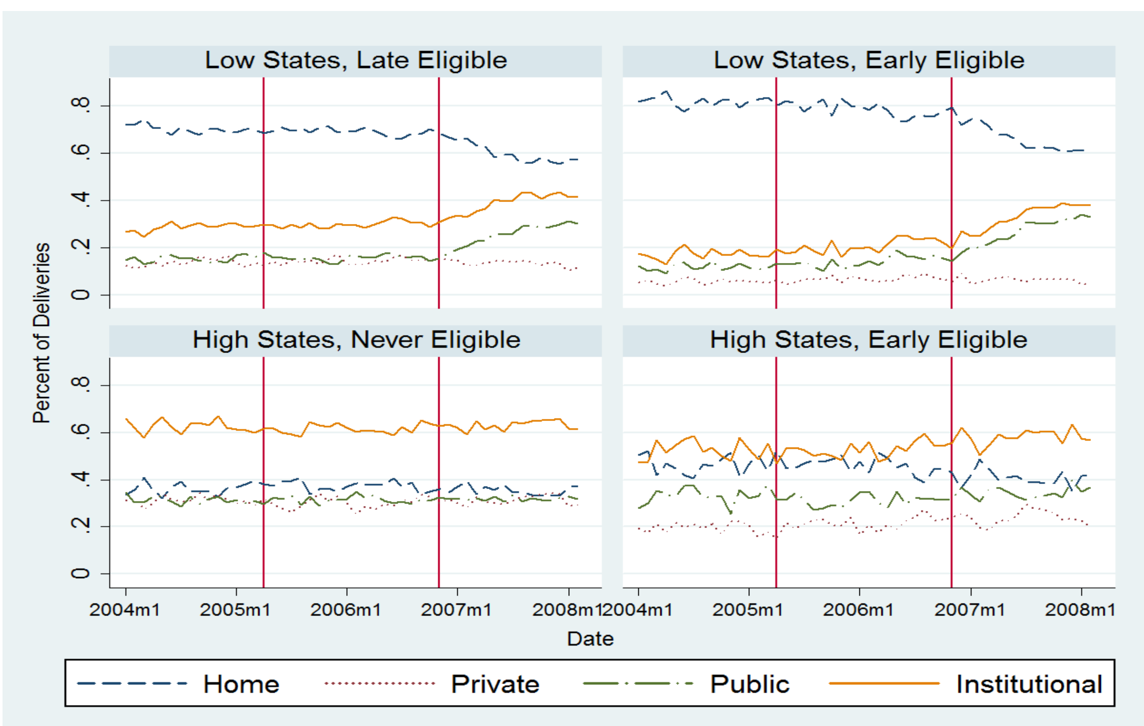


Table 2:
Summary Statistics for Household Characteristics and Delivery

	Low Performing States				High Performing States			
Covariates	Mean	Median	S.D.	Obs.	Mean	Median	S.D.	Obs.
Household Characteristics								
BPL (%)	0.316	0	0.465	135,434	0.315	0	0.464	79,515
SC (%)	0.188	0	0.391	133,878	0.195	0	0.396	78,430
ST (%)	0.151	0	0.358	133,878	0.239	0	0.426	78,430
Rural (%)	0.866	1	0.341	136,098	0.757	1	0.429	80,381
HH Head Education (years)	4.571	4	4.738	136,028	5.559	5	4.785	80,195
Have Health Insurance (%)	0.025	0	0.157	134,611	0.048	0	0.215	79,148
Distance to Govt District Hospital (km)	39.271	35	26.089	105,069	43.389	36	29.781	57,113
Distance to Govt CHC (km)	23.131	15	22.516	107,242	20.449	14	22.101	55,719
Distance to Govt PHC (km)	10.735	8	11.630	102,931	11.504	8	14.331	50,327
Distance to Private Hospital (km)	22.855	15	21.766	107,289	24.517	15	26.535	54,219
Mother and Child Characteristics								
Age at Childbirth (years)	25.418	25	5.482	136,098	24.537	24	4.929	80,381
Eligible for JSY Transfer (%)	0.625	1	0.484	136,098	0.285	0	0.452	79,828
Child Delivered is Male (%)	0.534	1	0.499	136,044	0.540	1	0.498	80,346
Mother Sick in Last 3 Months (%)	0.274	0	0.446	136,097	0.200	0	0.400	80,381
Mother Sought Treatment if Sick (%)	0.311	0	0.463	36,939	0.381	0	0.486	15,467
Child Sick Last 2 Weeks (%)	0.306	0	0.461	131,544	0.291	0	0.454	78,495
Child Sought Treatment if Sick (%)	0.693	1	0.461	31,430	0.772	1	0.419	15,907
Delivery Characteristics								
Pre-April 2005 Delivery in Public Facilities (%)	0.141	0	0.348	20,156	0.318	0	0.466	13,368
Post-April 2005 Delivery in Public Facilities (%)	0.215	0	0.411	113,344	0.317	0	0.465	65,551
Pre-April 2005 Delivery in Private Facilities (%)	0.111	0	0.314	20,156	0.281	0	0.450	13,368
Post-April 2005 Delivery in Private Facilities (%)	0.115	0	0.319	113,344	0.281	0	0.450	65,551
Pre-April 2005 Delivery at Home (%)	0.738	1	0.440	20,156	0.390	0	0.488	13,368
Post-April 2005 Delivery at Home (%)	0.660	1	0.474	113,344	0.390	0	0.488	65,551
HH Borrowed/Sold Items to Afford Delivery (%)	0.312	0	0.463	133,494	0.263	0	0.440	78,900
Cost of Transportation to Facility (Rs.)	267.25	164	323.66	34,649	193.09	88.8	268.59	38,836
Cost at Public Facility, Normal Birth (Rs.)	1,138.3	739	1,418.6	20,649	1,319.9	815	1,693.7	17,659
Cost at Public Facility, Assisted/C-Section (Rs.)	3,955.1	2,341	4,130.0	3,082	3,975.7	2,880	3,798.4	3,466
Cost at Private Facility, Normal Birth (Rs.)	2,687.0	1,860	2,521.3	9,549	3,619.0	2,759	2,896.7	13,824
Cost at Private Facility, Assisted/C-Section (Rs.)	8,013.4	8,000	5,594.0	3,844	9,814.7	9,600	4,874.9	5,918
Cost for Home Delivery, Normal Birth (Rs.)	372.9	187	663.7	82,598	501.6	243	884.8	26,919
Cost for Home Delivery, Assisted/C-Section (Rs.)	583.3	234	1,223.5	625	569.4	246	1,276.2	269

Notes: Values for cost of transportation and delivery variables exclude the top one percent of outliers. Cost variables are adjusted using monthly inflation rates to be in terms of January 2004 Rupees.

Our model in section 4 incorporates how individuals' prior expectations over facility quality affect facility choices, as well as considers how individuals update these expectations after utilizing a particular facility. To test the model's predictions, we construct measures of priors and signals for each woman that gives birth in our data. Few variables in the DLHS-III speak to pre-birth beliefs, though we are able to construct measures of priors by assigning point values to answers regarding experiences with facilities before giving birth (see Appendix Table A1). Since this construction is somewhat arbitrary, we provide two different measures of priors, showing results with both measures. The first measure places more weight on advice and services provided by facilities, while the second puts more weight on one's overall impression of facility care. Since survey questions do not specify expectations between private and public facilities, priors are for all facilities in general relative to come care.

After utilizing a facility, women may revise their beliefs of facility quality based on their most recent experience. We similarly calculate a measure for signals regarding one's experience at a facility during childbirth based on the number of complications during, and services and advice given after, delivery.[7] We normalize both signals and priors to be mean zero and with standard deviation equal to one.

4 Theoretical Model of Facility Choice

This section lays out our theoretical framework for understanding why facility choice at the time of childbirth may affect future health care seeking behavior. We provide a two-period, random utility model that allows for both learning about facility quality and paying one-time experience costs.[8] The model is meant to, first, show how JSY affects delivery locations, and second, help distinguish between these two possible mechanisms that would cause delivery facility choice in one period to influence future decisions. We finalize this section with predictions and results to be empirically tested.

4.1 Setup

Women are pregnant in the initial period ($t = 1$), and they, or their children, may have a separate illness in a later period ($t = 2$). In each period women must make the decision of which facility to utilize for medical care. Agents are forward-looking such that they take into account how an initial period choice affects the utility of future choices when deciding upon a location in the first period. Individuals are Bayesian and update their beliefs about facility quality after utilizing a facility.

[7]One concern with using experiences at birth to construct signals is that experiences may be correlated with expectations. For instance, if a woman expects a difficult birth and receives satisfactory treatment, she may receive a relatively high signal while we assign her a low signal. This would result in defining more people to have revised down their expectations of quality.

[8]We omit an income effect here because we find no empirical support for such an effect. We expect any income effect to be small since the illnesses we analyze in the second period occur on average nearly 20 months after childbirth. Since the JSY transfer is not high frequency, we do not see this as an appropriate setting to test for reference dependence either.

Define w_{ijd}^t as an indicator for whether or not woman i in district d seeks treatment in facility j in period t, such that $\forall t \in \{0, 1\}$, $w_{ijd}^t = 1$ if the mother uses facility j in period t and equal to 0 otherwise (further denote w_{id}^t to be the chosen location). We assume women have three alternatives from which to choose ($J = 3$): a public facility ($j = 1$), a private facility ($j = 2$), or home treatment ($j = 3$). Each woman has an initial prior over facility j's quality (relative to home treatment) which incorporates facility characteristics that may affect one's treatment experience. Priors are assumed to be normally distributed with mean μ_{ijd} and variance $\sigma_{j\mu}^2$. If a woman delivers in facility j in $t = 1$ she receives a noisy and private signal (θ_{ijd}) over that facility's quality, but receives no information about non-chosen alternatives.[9] This signal is defined as:

$$\theta_{ijd} = q_j + \zeta_{ijd},$$

where q_j is facility j's true quality, and the signal noise is assumed to be normally distributed [$\zeta_{ijd} \sim N(0, \sigma_{j\zeta}^2)$] and independent across individuals. These signals can be interpreted in a variety of ways, including: observations about facility cleanliness, maintenance, and infrastructure; degree of attention and comfort given by medical staff to the patient; ability of medical staff to handle unexpected events that arise while receiving care; etc. Women may also be reluctant to go to a formal medical facility if they think staff will refuse to admit and care for them. Thus, priors and signals can also be thought of as incorporating people's expectations over admission probabilities.

Given one's prior and signal, private updating over quality in $t = 2$ is given by:

$$\mathrm{E}_i[q_j|\mu_{ijd}, \theta_{ijd}] = \alpha_i \theta_{ijd} + (1 - \alpha_i)\mu_{ijd}, \tag{4.1}$$

where the weight on the signal equals:

$$\alpha_i = \frac{w_{ijd}^1 \cdot \sigma_{j\mu}^2}{w_{ijd}^1 \cdot \sigma_{j\mu}^1 + \sigma_{j\zeta}^2}.$$

Following standard methods of Bayesian learning, women thus place more weight on their signal the higher is the variance in the prior over quality ($\sigma_{j\mu}^2$) and the lower is the degree of noise in the signal ($\sigma_{j\zeta}^2$). However, since women only receive a signal for facility j if they utilized it in $t = 1$, the posterior expected quality in $t = 2$ will be different than the prior only if $w_{ijd}^1 = 1$ (and there is non-zero variance in priors).

[9] While in practice information about facility quality may diffuse through other channels (*e.g.* through neighbors and relatives), this framework limits belief formation to be based only on personally obtained information.

We then define U^t_{ijd} to be woman i's (ex-ante) period-specific utility from choosing facility j. Decomposing utility into its expected (v) and unobserved (ϵ) factors we have:

$$
\begin{aligned}
U^t_{ijd} &= \mathrm{v}^t_{ijd} + \epsilon^t_{ijd} \\
&= \gamma^t_{id}\mathrm{E}_i[q_j] - c^t_{ijd} - \lambda^t_{jd}(w^{t-1}_{id}) + \epsilon^t_{ijd}.
\end{aligned} \tag{4.2}
$$

Here, γ^t_{id} is a scale parameter indicating the severity of one's medical condition. A larger γ puts more weight on expected quality relative to other utility components, thus if expected quality of facility j is sufficiently high, a higher γ increases the probability of treatment being sought in that facility. $\lambda^t_{jd}(w^{t-1}_{id}) \geq 0$ represents the non-monetary, experience costs of utilizing a facility (figuring out its location, learning about administrative and bureaucratic procedures, etc.). This cost only needs to be paid once, so it is a function of previous facility choice. For example, if a private facility is chosen in both periods, then $\lambda^2_{2d}(w^1_{id} = 2) = 0$, but if a public facility is chosen in the second period after private delivery in the first, $\lambda^2_{1d}(w^1_{id} = 2) > 0$. c^t_{ijd} represents the out-of-pocket costs to an individual for utilizing facility j, and we further define costs as:

$$
c^t_{ijd} = \begin{cases} p^t_{ijd} - \mathbb{1}(eligible_i)\mathbb{1}(exist^t_d)\mathbb{1}(j=1)\cdot JSY_{id}, & \text{if } t=1 \\ p^t_{ijd}, & \text{if } t=2, \end{cases}
$$

where p^t_{ijd} is out-of-pocket expenses for facility treatment (treatment fees plus transportation costs) relative to home delivery, and the second term includes indicator variables each equal to one if woman i is eligible for the JSY transfer, JSY exists in her district at time t, and she chooses a public facility, respectively. If all three conditions are met then the JSY cash transfer, JSY_{id}, also factors into expected utility.[10] Since JSY is a public program primarily encouraging births in public facilities, for simplicity we assume the transfer can only be received if utilizing a public facility. Receiving benefits at private facilities was more difficult, and some women were only eligible in the public sector.[11] Lastly, ϵ^t_{ijd} is a random variable representing individual preferences for facilities and is assumed to be distributed type-1 extreme value and independently across mothers and facilities. Since expected quality

[10] We make the simplifying assumption that women fully expect to receive the entitlement conditional on eligibility and that they have full information regarding the terms of the transfer. In practice, however, some may meet program requirements, but due to distrust in institutions have a non-zero expectation that they will not receive their entitlement; others may not know if they meet eligibility criteria. Estimates indicate that only between 65 and 82 percent of deserving mothers received the JSY transfer in from 2007-08 (UN Popultion Fund (2009); Comptroller and Auditor General of India (2008)). This assumption then understates expected costs for public facilities, thus overstating mothers' willingness to choose them.

[11] For example, even by mid-2013, 11 states did not have any private facilities accredited under the program, and 7 more states had fewer than 20 accredited facilities state-wide.

and prices are relative to home treatment, and no experience costs need be paid if choosing home treatment, $U^t_{i3d} = \epsilon^t_{i3d}$.

4.2 Facility Choices

Since women are forward looking we further analyze facility choices in each period by backwards induction.

4.2.1 Second Period Choices

After giving birth in the initial period, women (or their children) may experience illnesses in the future ($t = 2$). If so, they must decide whether or not to seek treatment and at which facility. These illnesses are assumed to be independent across individuals and uncorrelated with facility choice in the initial period. We assume expected quality is constant across all medical needs, but the importance of expected quality to expected utility is allowed to vary based on the seriousness of the condition. At the start of the second period illness severity is revealed to the mother, and conditional on her facility choice in the first period she chooses the facility that maximizes her second period utility, *i.e.* $max_j(U^2_{ijd}(w^1_{id}))$. Given the distributional assumption on ϵ^2_{ijd}, the probability that facility j is chosen in the second period, conditional on being ill and first period choice, is:

$$\begin{aligned} \Pr(w^2_{ijd} = 1 | w^1_{id}, \gamma > 0) &= \Pr\big(U^2_{ijd}(w^1_{id}) \geq U^2_{ij'd}(w^1_{id})\big) \qquad \forall j' \neq j \\ &= \frac{e^{\left(\gamma^2_{id}\mathrm{E}_i[q_j] - c^2_{ijd} - \lambda^2_{jd}(w^1_{id})\right)}}{\sum_{k=1}^{3} e^{\left(\gamma^2_{id}\mathrm{E}_i[q_k] - c^2_{ikd} - \lambda^2_{kd}(w^1_{id})\right)}}, \end{aligned} \tag{4.3}$$

where $\mathrm{E}_i[q_j]$ is a function of priors and any signal received in the first period. Note that the JSY transfer does not directly impact second period choice probabilities, but does so indirectly by increasing the utility of public facility delivery in the initial period.

Our goal is to examine how facility choice in the first period affects future facility choice. To asses whether any effects we find are driven by paying one-time experience costs or learning about facility/clinician quality, we analyze, without loss of generality, the difference in probability of choosing public treatment in the second period between those that also chose public delivery in the first period and those that chose home delivery. This comparison yields (where we drop subscripts i and d for ease of exposition):

$$\begin{aligned} & \Pr(w^2 = 1 | w^1 = 1) > \Pr(w^2 = 1 | w^1 = 3) \\ \iff \quad & \gamma^2 \alpha(\theta_1 - \mu_1) + \lambda^2_1 > 0. \end{aligned} \tag{4.4}$$

If this inequality holds, people who utilized public delivery in the initial period are more likely to also utilize public facilities in the later period relative to those that chose home delivery. Inequality (4.4) indicates this result can be caused by updating (θ_1 and μ_1) or paying experience costs (λ_1^2).

4.2.2 First Period Choices

In the first period, women are uncertain about whether or not they (or their children) will become ill in the second period. For analytical simplicity, suppose that with probability $\pi_{id} \in [0,1]$ woman i (or her child) becomes ill in $t = 2$, and that conditional on being ill, expected illness severity (γ_{id}^2) is known. If no illness occurs no treatment facility is chosen. Since actual illness status is revealed only in the second period, in the initial period women have expected utility of the second period choice equal to:

$$\mathrm{E}_i\big[max_j(U_{ijd}^2(w_{id}^1))|\pi_{id}\big] = \pi_{id}\big[\ln\big(\sum_{j=1}^{3} e^{(\mathrm{v}_{ijd}^2(w_{id}^1))}\big) + \kappa\big],$$

where $\mathrm{v}_{ijd}^2(w_{id}^1) = \gamma_{id}^2\mu_{ijd} - c_{ijd}^2 - \lambda_{jd}^2(w_{id}^1)$ are known factors of utility, κ is Euler's constant, and the expression is derived from the log-sum formula (see Williams (1977); McFadden (1978)). To the econometrician, the total (ex-ante) expected discounted utility from choosing facility j for childbirth in $t = 1$, $V_{id}(j)$, then equals:

$$V_{id}(j) = U_{ijd}^1 + \delta\pi_{id}\ln\big(\sum_{k=1}^{3} e^{(\mathrm{v}_{ikd}^2(w_{id}^1))}\big), \tag{4.5}$$

where $\delta \in (0,1)$ is the discount factor, and we omit κ due to its analytical irrelevance. A mother thus chooses delivery facility alternative j in the initial period to maximize equation (4.5).

Given the distributional assumption on ϵ_{ijd}^1, the probability that facility j is chosen for childbirth is:

$$\begin{aligned}\Pr(w_{ijd}^1 = 1) &= \Pr\big(V_{id}(j) \geq V_{id}(j')\big) \qquad\qquad \forall j' \neq j \\ &= \frac{e^{\left(\gamma_{id}^1\mu_{ijd} - c_{ijd}^1 - \lambda_{jd}^1 + \delta\pi_{id}\ln\left[\sum_{k=1}^{3} e^{(\mathrm{v}_{ikd}^2(w_{id}^1))}\right]\right)}}{\sum_{j=1}^{3} e^{\left(\gamma_{id}^1\mu_{ijd} - c_{ijd}^1 - \lambda_{jd}^1 + \delta\pi_{id}\ln\left[\sum_{k=1}^{3} e^{(\mathrm{v}_{ikd}^2(w_{id}^1))}\right]\right)}}.\end{aligned} \tag{4.6}$$

If women were myopic the last term in the exponents would be omitted from equation (4.6). The forward-looking assumption, however, implies that women know that initial period choices influence second period utilities.

4.3 Model Implications

Using the framework laid out in the previous subsections, and deriving basic comparative statics on equations (4.3) and (4.6) and inequality (4.4), we formulate a number of predictions and results regarding facility choice in each period (function forms of the derivatives are shown in Appendix section 8.1). These are:

Prediction 1. $\frac{\partial Pr(w^1_{id}=1)}{\partial JSY_{id}} > 0$, $\frac{\partial Pr(w^1_{id}=\{2,3\})}{\partial JSY_{id}} < 0$. *JSY increases the probability of public delivery in the first period and lowers both the probabilities of private and home delivery. This effect of JSY is thus stronger in low states and during the late program period (where the transfer is larger), but only for eligible women.*

Prediction 2. $\frac{\partial Pr(w^1_{ijd}=1)}{\partial \mu_{ijd}} > 0$ *for* $j \in \{1,2\}$. *First period institutional delivery is positively correlated with priors on quality.*

Prediction 3. $\frac{\partial Pr(w^1_{ijd}=1)}{\partial \pi_{id}} > 0$ *if* $\lambda_{jd} > 0$ *for* $j \in \{1,2\}$, *but* $\frac{\partial Pr(w^1_{ijd}=1)}{\partial \pi_{id}} = 0$ *if* $\lambda_{jd} = 0\ \forall j$. *The probability of institutional delivery in the first period increases with the likelihood of being ill in the second period so long as experience costs are non-zero.*

This comes from the fact that the more likely a woman is to need medical treatment in the future, the more willing she will be to pay experience costs in the first period since doing so raises the relative utility of choosing that same facility again in the future.

Prediction 4. *If* $\theta_{ijd} > (<)\ \mu_{ijd}$ *quality expectations are revised upward (downward), increasing (decreasing) the probability of selecting treatment at facility* j *in the second period. The extent of belief revision is dependent upon the relative size of the variances in the prior and signal.* θ_{ijd} *may be* $\gg \mu_{ijd}$, *but if* $\sigma^2_{j\zeta} \gg \sigma^2_{j\mu}$ *the extent of updating is muted.*

Result 1. *First period facility choice impacts second period choice through learning about quality and paying experience costs. From inequality (4.4), if people weakly revise down their quality expectations after the first period* ($\theta_1 \leq \mu_1$), *yet* $Pr(w^2 = 1|w^1 = 1) > Pr(w^2 = 1|w^1 = 3)$, *then* λ^2_1 *must be greater than 0 and the effect of having already paid one-time experience costs is present. Alternatively, if people strictly revise down their quality expectations* ($\theta_1 < \mu_1$), *and* $Pr(w^2 = 1|w^1 = 1) < Pr(w^2 = 1|w^1 = 3)$, *then the effect of learning about quality dominates any effect of paying experience costs.*

From a policy perspective, it is important to know if JSY has the indirect benefit of improving health care utilization in India. We use the intuition developed here to better understand the mechanisms driving the empirical results that follow.

5 Empirical Strategy

5.1 Choices of Delivery Facilities

The previous section highlights factors that affect women's choices of delivery locations, namely beliefs about quality, costs, and expectations about future illnesses. To analyze the effects of JSY on institutional delivery, we use its introduction in 2005 as an exogenous shock to women's expected utilities for delivery at each facility. Those who gave birth prior to JSY chose facilities partially due to medical fees at each facility, but once JSY became available the costs many women faced at public facilities fell precipitously. Proper identification of JSY's effect requires a valid control group. We handle this by exploiting the program's individual-level variation in eligibility and regional-level changes in cash incentives in late 2006, but our primary source of identification is the cross-sectional and temporal variation in JSY's introduction across India's districts. We demonstrate below that the timing of district-level program adoption is quasi-random and exogenous to other factors that may influence facility choice.

Using the three above-mentioned sources of variation, we test Prediction 1 by estimating the following equation by multinomial logit:

$$y_{ijmd} = \beta_{0j} + \beta_{1j}(\text{JSY Implemented})_{md} + \beta_{2j}p_{ijmd} + X'_{ijmd}\beta_{3j} + \eta_s + \rho_m + v_{ijmd}, \tag{5.1}$$

where y_{ijmd} represents an underlying latent index of utilities for each facility alternative j of women i in district d and month m, JSY Implemented$_{md}$ is an indicator variable for the program being in existence in one's district at the time of childbirth, p_{ijmd} is total out-of-pocket expenses (facility plus transportation charges), X'_{ijmd} is a vector of individual and household characteristics, and η_s and ρ_m are state and month dummies, respectively.[12] Home births is used as the base category. With program treatment at the district level and the included fixed-effects, this specification estimates how JSY impacts facility choice within a given state and month for women living in a district where JSY was adopted relative to those living in non-JSY districts. Thus the parameter of interest is β_{1j}. We also estimate specifications which include dummy variables for eligibility (Eligible), being in a low state (Low St.), giving birth in the later period of JSY after program incentives increased (Post Nov. 2006), and a full set of interactions of these terms. Although the framework in section 4.2 suggests that priors of each facility's quality should influence mother's decisions, we are only able to construct priors for all types of medical facilities as a whole, *i.e.* public and private

[12] The mean (median) number of observations per state-month group is 365 (224), so inconsistency of the estimates is not a primary concern.

facilities together. To test Prediction 2 we thus estimate the following equation by probit:

$$\begin{aligned} y_{imd} = \alpha_0 + \alpha_1(\text{JSY Implemented})_{md} + \alpha_2(\text{Prior})_{imd} \\ + \alpha_3(\text{JSY Implemented} \times \text{Prior})_{imd} + \alpha_4 p_{imd} + X'_{imd}\alpha_5 + \eta_s + \rho_m + \nu_{imd}, \end{aligned} \tag{5.2}$$

where y_{imd} equals 1 if woman i selects institutional delivery (public or private) and 0 otherwise, Prior_{imd} is our constructed value of priors over facility quality, and all other variables are analogous to equation (5.1).

5.2 Choices of Post-Delivery Facilities

We aim to quantify the impact of using a formal health care facility on future treatment decisions to see whether in this context short-run incentive programs can have long-lasting impacts on health-seeking behavior. Predictions 3 and 4 indicate that previous facility usage changes the relative probabilities of future usage. We first outline the empirical strategy to test if this effect is present and then aim to distinguish between possible mechanisms.

We regress treatment at a formal medical facility (either public or private), conditional on recently being ill, on past facility use. With binary variables for the outcome of interest, treatment status, and our instrument, we estimate the following equation by bivariate probit[13]:

$$Treatment_{imd} = \gamma_0 + \gamma_1(Exposed)_{imd} + X'_{imd}\gamma_2 + \eta_s + \rho_m + \epsilon_{imd}, \tag{5.3}$$

where $Treatment_{imd}$ is an indicator variable equal to 1 if women i (or her child) uses institutional treatment when recently sick and equal to 0 if no treatment is received or care is only given at home, $Exposed_{imd}$ is an indicator variable equal to 1 if women i was recently exposed to (delivered her most recent child in) a public medical facility, and all other variables are analogous to equation (5.1).[14] The DLHS-III provides data on recent illness episodes for both women and their children.[15] Recent illnesses occur on average 19.9 months after women

[13]Equations (5.3) and (5.4) are estimated by bivariate probit and the conditional mixed process estimator (CMP) (see Roodman (2011)). CMP aids in maximum-likelihood estimation and calculation of marginal effects for interaction terms when one of the interacted variables is being instrumented. Parameter restrictions are imposed on all variables except for interaction terms when multiple equations are included.

[14]Since JSY is a public program primarily encouraging births in public facilities, we define exposure as utilizing public facilities. Receiving JSY benefits at private facilities was more difficult, and some women were only eligible in the public sector. Further, by mid-2013, 11 states did not have any private facilities accredited under the program, and 7 more states had fewer than 20 accredited facilities each. Though we do not have this data for 2004-08, even fewer private facilities would have been accredited at that time.

[15]For children a recent illness is defined as having a fever or cough in the two weeks prior to being interviewed. We define a woman as having a recent illness if she claims to have any of ten different medical problems during the three months preceding interview, including: lower backache; non-menses abdominal

delivered their most recent child, thus we consider these episodes to be independent of one's experience at childbirth such that a new decision must be made of whether or not to seek treatment.

Exposure to public facilities, however, is likely correlated with factors unobserved by the econometrician, including preferences for facility types, how much a mother values her and her child's health, and expectations regarding future illness probabilities and the need for recurring use of medical facilities. If some women value their health more highly and believe medical facilities are beneficial, an uninstrumented regression of equation (5.3) likely would lead to an overestimate of γ_1. On the other hand, this parameter would be biased downward if some women had low expectations of future needs for facilities and so did not utilize institutional delivery because of relatively high experience costs, but then later unexpectedly fell ill. To deal with these sources of selection bias we instrument for exposure using an indicator variable for whether or not JSY existed in the mother's district at the time of childbirth. Estimation of delivery locations from equation (5.1) is then similar to a first-stage regression for the instrumented regression in equation (5.3). As shown below we find large and significant effects of JSY's existence at the time of childbirth on exposure to public medical facilities.

We believe this is a valid instrument since the timing of JSY's introduction within a given state is plausibly random and uncorrelated with many factors that would influence facility choice for childbirth and for future illnesses (see section 5.3). An additional requirement to satisfy the exclusion restriction is that medical facilities in JSY districts did not improve over time relative to those in non-JSY districts due to NRHM investments. We test this by regressing the change in a district's public facility quality from 2003 to 2007-08 on the length of time that JSY operated in that district. Results are shown in Appendix Table A3, which show that the length of JSY's existence is unrelated to changes (improvements) in public facility quality that may induce future facility take-up.

Our theoretical framework suggests that exposure to public facilities could influence future treatment decisions though either learning about clinician quality or paying one-time experience costs. To test Result 1, we estimate a variation of equation (5.3) where we interact institutional delivery with the direction of women's updating about facility quality. Specifically, we estimate by bivariate probit:

$$\begin{aligned} Treatment_{imd} = \psi_0 &+ \psi_1(Inst. \times Revise\ Up)_{imd} + \psi_2(Inst. \times No\ Revision)_{imd} \\ &+ \psi_3(Inst. \times Revise\ Down)_{imd} + X'_{imd}\psi_4 + \eta_s + \rho_m + \varphi_{imd}, \end{aligned} \tag{5.4}$$

where $Treatment_{imd}$ is the same as above, $Inst.$ is an indicator variable equal to 1 if mother

pain, pain during urination or defecation; swelling of or lesions around the groin; and pain from intercourse.

i's most recent childbirth occurred at a formal medical facility, which we interact with the direction of updating about facility quality. Home delivery is the omitted category (for which no updating is made regarding facility quality). Since we only have measures of signals and priors for all facilities as a whole, the independent variables in this estimation are not facility-specific. We estimate equation (5.4) separately for women and children, and also run specifications where we control for illness severity and length of time between facility choices. By Result 1, a positive value for ψ_2 and ψ_3 would suggest experience costs affect future facility use since these women would be more likely to use facilities even though they (weakly) revised down their quality beliefs. A negative ψ_3 would suggest learning about quality dominates any effect of paying experience costs.

5.3 Estimation of District-Level Program Start Dates

The empirical strategy outlined above relies upon the use of exogenous variation in district-level JSY start dates. We show that most districts did not implement the program in April 2005, but instead experienced long delays in adoption, which are uncorrelated with many factors that affect facility choice.

5.3.1 Mean-Shift Model

Proper implementation of the NRHM and JSY involved setting up State Health Societies to actually carry out reforms at the state level (GOI (2005a)). From administrative records we construct a timeline of when each state officially constituted State Health Societies by approving the Center's Memorandum of Association and Bylaws for the NRHM.[16] Appendix Table A2 lists each state's approval date, which shows that it took almost a year for all states to formally agree to initiate programs under the NRHM. In addition, States were required to carry out reforms under a decentralized arrangement with their own districts, setting up District Health Societies to implement program components locally, where District managers were given full power to distribute funds to hospitals, medical officers, and any other implementing agencies (GOI (2014)). Given this institutional framework, we define the district as the level of treatment under JSY, and expect within-state variation in the timing of JSY's implementation if District Health Societies did not all form at once.

Following Bai (1994) and Munshi and Rosenzweig (2013) we formally identify in which month each district implemented JSY by applying least squares to estimate a change-point

[16] Official documents dating Bylaw approval dates are unavailable for three states. For Sikkim we use the month that that NRHM was launched in India's Northeastern States. For Orissa we use the date mentioned in an audit study by the International Labour Organization. We are unable to find specific information for Kerala, and therefore we only set April 2005 as a lower bound on district-level start dates for this state.

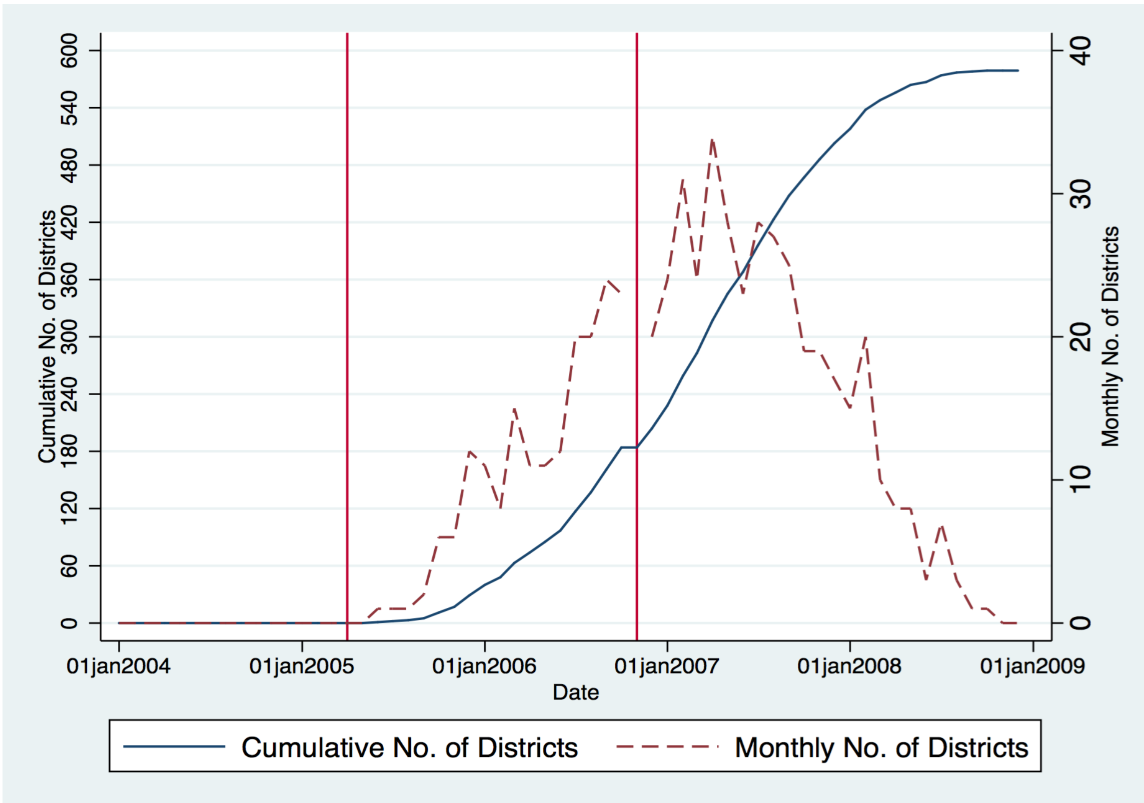
in the percent of women receiving the JSY cash transfer. We regress, separately for each district and each potential start month, the percent of women receiving the cash transfer on a hypothetical post-period dummy variable.[17] Defining $\underline{t}$ as the true district-level start date, the least squares estimate of $\underline{t}$, $\hat{\underline{t}}$, is chosen as the $\hat{\underline{t}}$ that minimizes the residual sum of squares among all possible sample splits (τ), *i.e.* $\hat{\underline{t}} = argmin_{\tau}[RSS(\tau)]$. The change-point month is thus identified as the date which yields the largest mean-shift in receipt of JSY funds out of all possible dates. Following Hansen (1999), we test the significance of each district's $\hat{\underline{t}}$ using a likelihood ratio test, with the test statistic calculated as: $LRT(\tau) = \frac{RSS(\tau)-RSS(\hat{\underline{t}})}{RSS(\hat{\underline{t}})} \times N$ (see Appendix section 8.2 for complete details on this procedure). On average across all districts the structural break is relatively precisely estimated; weighting districts by number of births, the confidence bounds for the estimated dates are [-2 months, 2 months] and [-1 month, 1 month] for 95 percent and 90 confidence intervals, respectively (see Appendix Figure A2).

Estimates show districts took between 0 and 39 months to implement JSY from their states' approval of the Center's NRHM Bylaws, and on average 23.1 months from April 2005. Figure 3 shows the number of districts implementing JSY in each month, as well as the cumulative number of implementing districts over time. Appendix Figure A1 depicts a map of Indian districts color-coded by delay in JSY adoption after April 2005. From this map it is clear that variation in start dates exists both within and across states. In broad terms, southern states (which are mostly high performing states) were faster at implementation than the northern and central states (predominantly low performing states).

We perform two additional analyses to validate this estimation. First, for results to be consistent with the story that districts implemented JSY at the estimated change-point month, the percent of women choosing institutional births should also increase discontinuously at these dates. Consistent with the institutional delivery patterns seen in Figure 1, we find that in low states institutional delivery significantly increases at the same estimated JSY start dates, but insignificantly in high states (see Appendix Figure A3 and the Appendix section 8.3 for further discussion). Second, we verify that the rise in receipt of the cash transfer (the outcome variable in the mean-shift model) is not driven by changes in the composition of mothers giving birth. If birth rates rose for women eligible for maternal benefits but fell for ineligibles, it is possible that the mean-shift model is simply picking up these movements in composition. We do not find, however, any changes in birth mother composition at the same time as the estimated start-dates (see Appendix Figure A4).

[17] The DLHS-III asks whether women received any government financial assistance for delivery under JSY or any state-specific scheme. This wording was chosen since JSY took local language names in some states, but it also induced positive responses for people that received funds under the NMBS. As a result, 4.4 percent of women report receiving a transfer before April 2005. The monthly percent of women reporting this is constant, however, up through April 2005. Since there were no other maternal benefit schemes initiated at this time, any uptick in positive response rates to this question we attribute to JSY becoming operational.

Figure 3:
Number of Districts Having Implemented JSY Over Time



While on average across all districts the estimated dates are precisely estimated, this is not the case for all districts individually. Using a 90 percent confidence interval 197 out of 581 districts (33.9 percent) do not see a statistically significant change in the percent of women receiving maternal delivery benefits over time. In Appendix section 8.4 we discuss three plausible explanations. We conclude this is likely caused by program mismanagement and budgetary bottlenecks in certain districts that inhibited program funds from being distributed to all eligible mothers, even though the program was technically in existence. Based on this we use the estimated district-level start dates from the mean-shift model regardless of whether or not the estimated break date is significantly different from all other dates.

5.3.2 Testing for the Exogeneity of District-Level Start Dates

We propose to exploit the variability in program implementation across time and space to identify the causal effect of JSY on use of medical facilities. The main threat to this methodology's validity is that the timing of program implementation may be correlated with district characteristics which also are related to mothers' choice of medical facilities. We identify seven categories of factors which may be correlated with both the timing of program adoption and women's use of medical facilities, and show that that, within a given state, a district's JSY start date is uncorrelated with these factors. District-level factors we analyze include: pre-JSY rates of institutional delivery; socio-economic characteristics such as urbanicity and wealth; availability of public and private medical facilities; people's preferences for health investments[18]; ethnic fractionalization[19]; extent of female political representation; and political party affiliation among MLAs[20] (see Appendix section 8.5 for a detailed discussion of why these factors are selected for analysis).

To assess if these factors are related to the timing of program implementation we estimate a discrete-time hazard model of the probability of program adoption. We regress whether or not a district implemented JSY in a given month on a full set of district characteristics by logit. Traditional non-linear probability models assume duration independence, *i.e.* the probability of surviving or failing at any point in time is the same. However, since a district's action in one month is dependent upon is past actions, we allow for duration dependence by including a non-linear spline function in the logit equation[21] (see Appendix section 8.6 for additional details).

Marginal effects from the hazard model are shown in Table 3. Without controlling for state fixed effects (column 1) a higher rate of pre-JSY institutional delivery and the proportion of female politicians are positive predictors of implementation, whereas wealth and the percent of households who treat their water are negative predictors. Even though these effects are statistically significant, the magnitudes are small. For example, a 1 s.d. (60.1 percent, or 24.8 percentage points) increase in the pre-JSY institutional delivery rate would result in a 0.06 s.d. (24.5 percent, or 1.5 percentage points) increase in the probability

[18]We use three measures of a district's relative preference for heath investments: the percent of households that regularly treat their drinking water; the percent of villages that have formed a Village Health & Sanitation Committee (VHSC); and the percent of villages that discussed health related issues at *Gram Sabha* meetings (public forums) in the year prior to being interviewed in 2008.

[19]We construct an ethnic fractionalization index for each district as: $EthnicFrac_d = 1 - \sum_i (caste_{id})^2$, where $caste_{id}$ is the percent of households in district d belonging to caste group i. Caste groups include upper caste, scheduled caste, scheduled tribe, other backward class, Muslim, and other.

[20]We use two measures of political party allegiance: first, the percent of MLAs that belong to the Indian National Congress (INC, same party that headed the Central government and initiated the NRHM), and second, the percent of MLAs that belong to the same party as their state's Chief Minister.

[21]Splines allow for a smoothed baseline hazard probability over predetermined intervals, and estimated coefficients on the intervals help trace out the path of duration dependence. Following MaCurdy *et al.* (2014) we specify the spline as: $f(t, \alpha) = \sum_{j=1}^{J} [\Phi_{j-1}(t) - \Phi_j(t)] \cdot \alpha_j$, where $\Phi_j(t)$ represents the CDF of a normal random variable with mean μ_j and variance σ_j^2 for interval j in time t, and α_j denotes a parameter vector. Appendix Figures A5 and A6 show that the logit specification with splines fits the raw data well, but the model without splines over- and under-predicts the adoption probability over various time intervals. The non-monotonicity of duration dependence is evident in both figures; while the model without the spline function predicts a decreasing probability of adoption over the relevant interval, the model with the spline allows for both increasing and decreasing probabilities over different time intervals.

Table 3:
Discrete-Time Hazard Estimates of a District's Probability of Implementing JSY

Covariates	(1)	(2)
Pre-April 2005 Institutional Delivery Rate	0.054***	0.023
	(0.011)	(0.016)
% Rural HHs	0.015	0.014
	(0.015)	(0.021)
Average Wealth Index	-0.018***	-0.009
	(0.006)	(0.011)
% Households Treating Water	-0.014**	-0.000
	(0.007)	(0.012)
% Villages with VHSCs	-0.002	0.011
	(0.009)	(0.012)
% Villages Discussing Health at *Gram Sahab*	0.014	0.005
	(0.010)	(0.013)
Ethnic Fractionalization Index	-0.012	-0.012
	(0.013)	(0.017)
Public Hospital Beds Per Capita	-0.000	0.000
	(0.000)	(0.000)
Average Distance to Private Hospitals	-0.000	-0.000
	(0.000)	(0.000)
% Female Politicians	0.037***	0.038***
	(0.014)	(0.014)
% Politicians from INC	-0.004	-0.007
	(0.007)	(0.007)
% Politicians in Same Party as Chief Minister	0.001	-0.003
	(0.006)	(0.006)
Obs.	10,093	10,093
χ^2 Stat. for Joint Spline Significance	484.07***	528.06***
Includes Spline	Yes	Yes
State Fixed Effects	No	Yes

Estimates by logit. The dependent variable is an indicator equal to one if JSY was implemented in that month, and zero otherwise. Coefficients are marginal effects and standard errors, which are clustered at the district level, are listed in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

of a district adopting JSY in a given month. To put this into context, a 24.8 percentage point increase in pre-JSY institutional delivery is equivalent to a district moving in rank from the 10th percentile to the 50th percentile among all districts. Such a percentage point increase is also larger than the increase in institutional delivery from April 2005 through early 2008 in rural areas of low performing states, which are the regions that experienced the largest increase after JSY's introduction. When state fixed effects are included coefficients on almost all factors reduce in magnitude and lose their statistical significance; only the coefficient on the percent of female politicians remains as a significant predictor of program adoption. The practical size of this correlation, however, is also small. This coefficient from column 2 indicates that a 1 s.d. (178.1 percent, or 10.4 percentage points) increase in the mean level of female representation would lead to a 0.02 s.d. (7.2 percent, or 0.4 percentage points) increase in the probability of a district implementing JSY in a given month. At this time only 6.7 percent of MLAs across India were female, and only 35.0 percent of districts had at least one female MLA. Thus, while the point estimate is statistically significant, with such a small practical effect it is unlikely that this factor alone is playing the key role in the within-state variation in implementation dates we find.

One concern with the hazard analysis is that some states have a small number of districts and including state fixed effects (which are non-linear functions) with a spline function may result in inconsistent estimates. As an additional test for the exogeneity of JSY start dates we therefore regress by OLS the number of months it took each district to implement JSY after its state approved the NRHM Bylaws on the same twelve potentially influencing factors from Table 3. The first half of Appendix Table A4 shows bivariate (OLS) regressions for each factor, and two additional regressions with all factors included. All coefficients are statistically insignificant from zero except for the coefficient on the level of female political representation, and this coefficient is again practically small. Comparing columns 2 and 3 which include and exclude state fixed effects, respectively, we find a similar pattern as we did with the hazard model; including state fixed effects reduces the predictive power of most factors. To verify that the 33.9 percent of districts which do not have statistically significant changes in JSY beneficiaries are not driving the insignificance and small magnitude of these results, in the second half of Appendix Table A4 we replicate the analysis but limit the sample to only districts that were found to have a statistically significant JSY start dates. Again, only the extent of female representation in State Assemblies significantly impacts program timing, and the magnitude of the effect remains quite small.

The reduction in predictive power of these factors (observables) when including state fixed effects suggests that some unobservables for which we cannot account would also lose significance by looking at within-state variation in start dates. We take the OLS and hazard model results as evidence that the timing of JSY implementation within a state is quasi-random and plausibly orthogonal to district characteristics which may on their own affect mothers' use of health facilities. We exploit this variation as part of our identification strategy to estimate equations (5.1)-(5.4).

5.3.3 Additional Evidence For Start Date Exogeneity

The evidence provided above indicates that observable characteristics of districts' population, infrastructure, and political makeup are not capable of explaining the large within-state variation in JSY start dates across India. What then is driving this variation? Anecdotal evidence suggests that delays in program implementation are likely due to disagreements between implementing agencies, lack of information regarding program policies at the district level and block level, and budgetary bottlenecks. For example, in Rajnandgaon district of Chhattisgarh the State Health Society rejected the district hospital's proposal for fund utilization, initially delaying any NHRM programs (CBGA (2011)). Given that JSY is a Centrally-funded scheme with a highly decentralized strategy for implementation, funds were transfered first from the Center to State Governments, then further down to districts, blocks, and finally to primary health centers. In Chhattisgarh it took on average 229 days for funds to reach the block level during 2006-07 (CBGA (2011)). Such delays would impede the hiring of office staff, training of ASHA workers, and the commencement of payments to expectant mothers. In one southwestern district of Bihar, the District Manager took more than six months to hire a District Project Manager for the District Health Society because Center- and State-level politicians were pressuring him to hire their preferred candidate. In Uttar Pradesh, political instability in some areas led to implementation delays (Dagur *et. al.* (2010)). With respect to lack of information, most of the NRHM documents distributed to local bodies were in English, yet many district and block level offices would not have had English-proficient staff. These events are unlikely to be correlated with households' preferences for medical care utilization.

6 Program Effects

6.1 Effects on Delivery Location

We first report on the estimates of equations (5.1) and (5.2). Table 4 shows results from multinomial logit regressions of delivery location on the existence of JSY. Coefficients are marginal effects calculated at the mean value of independent variables. The first columns indicate that JSY increased institutional deliveries by 5.5 percentage points, with all of the increase occurring for public facilities, and no change in the usage of private ones. This is consistent with the fact that costs at public facilities are lower, as well as JSY being a government program that specifically encourages women to utilize public facilities. Receiving benefits at private facilities was often problematic and in some cases impossible, suggesting there may also be substitution away from private facilities in order to avail program benefits. The second columns examine effects by state type. Consistent with Prediction 1, here JSY is found to increase the probability of public facility delivery in low states by 14.8 percentage points, with 4.9 percentage points of this increase coming at the expense of private facilities. The main effect on JSY implementation is negative, indicating that home births actually increased in high states; but here we do not account for eligibility. The third set of columns indicates that eligible women in all states increased public facility deliveries by 12 percentage points. Ineligible women, however, experience a small, marginally significant reduction in public facility births. If capacity constraints are binding, the increase in usage by eligibles may have crowded out ineligible women. The fourth columns consider both state type and

Table 4:
Effects of JSY on Choice of Delivery Location

	(1)			(2)		
Covariates	Public	Private	Home	Public	Private	Home
JSY Implemented	0.053***	0.001	-0.055***	-0.061***	0.014	0.047***
	(0.012)	(0.008)	(0.013)	(0.011)	(0.011)	(0.016)
Low State × JSY Implemented				0.209***	-0.049***	-0.161***
				(0.014)	(0.010)	(0.016)
Obs.		172,946			172,946	
	(3)			(4)		
	Public	Private	Home	Public	Private	Home
JSY Implemented	-0.023*	0.005	0.018	-0.068***	0.004	0.063***
	(0.012)	(0.011)	(0.016)	(0.012)	(0.012)	(0.018)
Low State × JSY Implemented				0.177***	-0.035	-0.143***
				(0.028)	(0.023)	(0.030)
Eligible	0.024***	-0.029***	0.005	-0.021*	-0.030***	0.051***
	(0.009)	(0.006)	(0.009)	(0.012)	(0.010)	(0.014)
JSY Implemented × Eligible	0.120***	-0.013	-0.106***	0.039***	0.011	-0.050***
	(0.012)	(0.009)	(0.014)	(0.012)	(0.010)	(0.015)
Low State × Eligible				0.041***	0.008	-0.049***
				(0.013)	(0.010)	(0.015)
Low State × JSY Imp. × Eligible				-0.002	-0.010	0.012
				(0.029)	(0.023)	(0.029)
Obs.		172,946			172,946	
Includes Household Characteristics		Yes			Yes	
Month Fixed Effects		Yes			Yes	
State Fixed Effects		Yes			Yes	

Estimates by multinomial logit. The dependent variable is categorical for delivery location taking three possible alternatives: public, private, and home. Individual and household characteristics include: dummies for SC, ST, BPL status, having insurance, and rural/urban status; a set of dummies for wealth quintiles; out-of-pocket costs; mother's age at birth; distance to facilities; and years of education of the household head. Regressions include population sampling weights. Coefficients are marginal effects calculated manually to address the interaction terms, are calculated at the mean of the control variables. Robust standard errors, clustered at the district level, are listed in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

eligibility. Here, JSY is found to increase public facility deliveries in low states among eligibles and ineligibles by 14.6 and 10.9 percentage points, respectively, and decrease home deliveries for these populations by 11.8 and 8.0 percentage points, respectively. These large effects even for ineligibles should not be too surprising. Evidence of elite capture, leakage of funds, and people pretending to be eligible for benefits is widespread in many national government programs in India. For example, Niehaus *et. al.* (2013) find that 70 percent of households in Karnataka that are ineligible (based on a proxy means test) for food subsidies actually posses BPL cards which they can use to purchase these goods. Thus, women who are supposed to be ineligible for JSY benefits may have nevertheless been able to avail them. In fact, the percent of ineligible JSY women receiving maternity benefits rose from 5.4 percent before the program began to 10.6 percent thereafter. Lastly, in high states, eligibles and ineligibles actually increased home deliveries by nearly 1.3 and 6.3 percentage points, respectively.

These results show large and positive effects of JSY on increasing institutional delivery, with some substitution away from private facilities and towards public ones. To help validate these results we perform two sets of robustness checks. First, the most robust result from section 5.3.2 is that program implementation is positively correlated with prevalence of female politicians. Even though this correlation is small in magnitude, it is possible that the positive effects from Table 4 are driven by districts with female MLAs implementing the program earlier than others, and women from these districts having preferences that induce institutional delivery more so than women in other districts. We re-estimate the four specifications from Table 4 on a sub-sample of 366 districts (65.0 percent) that did not have any female MLAs during 2005-06. These results, shown in Panel A of Table 5, tell a very similar story to those above. The marginal effects are similar in magnitude to those for the whole sample, and their level of statistical significant is generally maintained. Such similarity in results should alleviate concerns of endogeneity with respect to district-level start dates. Second, we instead limit the sample to the 384 districts (66.1 percent) that have statistically significant estimated JSY start dates from the mean-shift model. Panel B of Table 5 shows results for this sub-sample. The effects here demonstrate the same types of substitution patterns, but the magnitudes of the marginal effects are noticeably larger. Inclusion of all districts in the main estimation, regardless of the significance in their estimated program dates, is then a more conservative estimate of JSY's effect on choices of delivery locations.

Prediction 1 also states that the effects of JSY should be larger in the later period of JSY's existence when cash incentives were increased. We test this prediction by re-estimating equation (5.1) now including a dummy variable (and interaction terms) that is equal to one if the delivery month is on or after November 2006. Results from this specification are shown in Table 6. The parsimonious regressing the first two sets of columns do not show any differential effect between the two program periods. In the third set of columns, which conditions on eligibility, JSY is found to decrease institutional deliveries in the late JSY period among ineligibles by 6.3 percentage points relative to the early period. Eligibles, on the other hand, were 3.0 percentage points more likely to utilize a medical facility when JSY was adopted in the later period relative to the early period. This is consistent with incentive amounts increasing after November 2006, and is further evidence of crowding out. The final regression in the fourth columns suggests the decreases and increases for ineligibles and eligibles, respectively, found in the third columns are driven by changes in low states only, but these coefficients are insignificant from zero.

From Prediction 2, individuals' priors over facility quality should also affect choice

Table 5:
Effects of JSY on Choice of Delivery Location, Only Select Districts

	Panel A - Only Districts Without Female MLAs											
	(1)			(2)			(3)			(4)		
Covariates	Public	Private	Home	Public	Private	Home	Public	Private	Home	Public	Private	Home
JSY Implemented	0.058***	0.007	-0.066***	-0.055***	0.023*	0.032*	-0.017	0.015	0.002	-0.061***	0.018	0.043**
	(0.014)	(0.009)	(0.014)	(0.014)	(0.014)	(0.019)	(0.014)	(0.013)	(0.018)	(0.015)	(0.015)	(0.021)
Low State × JSY Implemented				0.208***	-0.051***	-0.157***				0.169***	-0.040	-0.129***
				(0.017)	(0.013)	(0.019)				(0.033)	(0.028)	(0.034)
Eligible							0.020*	-0.019***	-0.001	-0.017	-0.017	0.034**
							(0.011)	(0.007)	(0.012)	(0.014)	(0.011)	(0.017)
JSY Implemented × Eligible							0.119***	-0.020*	-0.099***	0.029**	0.006	-0.035**
							(0.015)	(0.010)	(0.017)	(0.014)	(0.012)	(0.017)
Low State × Eligible										0.027*	0.006	-0.034*
										(0.016)	(0.012)	(0.019)
Low State × JSY Imp. × Eligible										0.017	-0.009	-0.009
										(0.035)	(0.027)	(0.034)
Obs.		110,426			110,426			110,426			110,426	
	Panel B - Only Districts With Statistically Significant JSY Start Dates											
	(5)			(6)			(7)			(8)		
JSY Implemented	0.076***	0.005	-0.081***	-0.074***	0.022*	0.051***	-0.029*	0.011	0.018	-0.086***	0.011	0.075***
	(0.014)	(0.010)	(0.014)	(0.014)	(0.012)	(0.017)	(0.015)	(0.013)	(0.018)	(0.015)	(0.013)	(0.019)
Low State × JSY Implemented				0.254***	-0.062***	-0.193***				0.236***	-0.064**	-0.172***
				(0.017)	(0.011)	(0.017)				(0.035)	(0.033)	(0.036)
Eligible							0.015	-0.032***	0.017	-0.023	-0.033***	0.056***
							(0.011)	(0.007)	(0.011)	(0.014)	(0.012)	(0.017)
JSY Implemented × Eligible							0.154***	-0.022**	-0.132***	0.037**	0.008	-0.046**
							(0.016)	(0.011)	(0.016)	(0.016)	(0.012)	(0.019)
Low State × Eligible										0.025	0.009	-0.034*
										(0.016)	(0.012)	(0.018)
Low State × JSY Imp. × Eligible										-0.007	0.012	-0.006
										(0.036)	(0.033)	(0.037)
Obs.		115,377			115,377			115,377			115,377	
Includes Household Characteristics		Yes			Yes			Yes			Yes	
Month Fixed Effects		Yes			Yes			Yes			Yes	
State Fixed Effects		Yes			Yes			Yes			Yes	

Estimates by multinomial logit. Panel A includes only the 366 (65%) of districts that had no female MLAs in April 2005, while Panel B includes only the 384 (66.1%) of districts that have an estimated JSY start month from the mean-shift model that is statistically different from all other start months. The dependent variable is categorical for delivery location taking three possible alternatives: public, private, and home. Individual and household characteristics include: dummies for SC, ST, BPL status, having insurance, and rural/urban status; a set of dummies for wealth quintiles; out-of-pocket costs; mother's age at birth; distance to facilities; and years of education of the household head. Regressions include population sampling weights. Coefficients are marginal effects calculated manually to address the interaction terms, and calculated at the mean of the control variables. Robust standard errors, clustered at the district level, are listed in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 6:
Effects of JSY on Choice of Delivery Location, by Early and Late JSY Periods

	(1)			(2)			(3)			(4)		
Covariates	Public	Private	Home	Public	Private	Home	Public	Private	Home	Public	Private	Home
JSY Implemented	0.063***	-0.019*	-0.044**	-0.015	-0.006	0.022	0.037**	-0.010	-0.027	-0.037*	-0.006	0.043
	(0.017)	(0.011)	(0.018)	(0.017)	(0.016)	(0.024)	(0.018)	(0.014)	(0.021)	(0.020)	(0.018)	(0.028)
Post Nov. 2006	-0.059	-0.037	0.096	-0.013	-0.043	0.056	-0.011	-0.038	0.049	-0.013	-0.040	0.052
	(0.137)	(0.194)	(0.132)	(0.140)	(0.205)	(0.133)	(0.150)	(0.217)	(0.138)	(0.145)	(0.210)	(0.132)
JSY Implemented × Post Nov. 2006	-0.013	0.028*	-0.015	-0.023	0.020	0.003	-0.081***	0.018	0.063**	-0.010	0.014	-0.004
	(0.024)	(0.015)	(0.019)	(0.020)	(0.020)	(0.031)	(0.024)	(0.018)	(0.031)	(0.025)	(0.019)	(0.034)
Low State × JSY Implemented				0.136***	-0.034	-0.102***				0.149***	-0.029	-0.120***
				(0.030)	(0.025)	(0.036)				(0.032)	(0.027)	(0.037)
Low State × Post Nov. 2006				0.081***	-0.021	-0.060*				0.100***	-0.020	-0.080**
				(0.018)	(0.024)	(0.032)				(0.027)	(0.026)	(0.040)
Low St. × JSY Imp. × Post Nov. 2006				0.025	0.003	-0.027				0.019	0.009	-0.028
				(0.035)	(0.041)	(0.059)				(0.057)	(0.047)	(0.063)
Eligible							0.016	-0.028***	0.012	-0.039***	-0.023**	0.063***
							(0.010)	(0.007)	(0.010)	(0.012)	(0.011)	(0.015)
JSY Implemented × Eligible							0.043**	-0.014	-0.029	0.059***	-0.001	-0.058**
							(0.020)	(0.016)	(0.020)	(0.023)	(0.018)	(0.028)
Post Nov. 2006 × Eligible							0.008	0.004	-0.012	0.011	-0.003	-0.008
							(0.020)	(0.028)	(0.025)	(0.030)	(0.030)	(0.023)
JSY Imp. × Post Nov. 2006 × Eligible							0.091**	0.002	-0.093*	-0.033	0.019	0.014
							(0.039)	(0.025)	(0.049)	(0.034)	(0.027)	(0.034)
Low State × Eligible										0.003	0.027**	-0.030*
										(0.013)	(0.013)	(0.016)
Low State × JSY Imp. × Eligible										-0.025	-0.030	0.055
										(0.047)	(0.047)	(0.043)
Obs		172,946			172,946			172,946			172,946	
Includes Household Characteristics		Yes			Yes			Yes			Yes	
Month Fixed Effects		Yes			Yes			Yes			Yes	
State Fixed Effects		Yes			Yes			Yes			Yes	

Estimates by multinomial logit. The dependent variable is categorical for delivery location taking three possible alternatives: public, private, and home. Individual and household characteristics include: dummies for SC, ST, BPL status, having insurance, and rural/urban status; a set of dummies for wealth quintiles; out-of-pocket costs; mother's age at birth; distance to facilities; and years of education of the household head. Regressions include population sampling weights. Coefficients are marginal effects calculated manually to address the interaction terms, and calculated at the mean of the control variables. Robust standard errors, clustered at the district level, are listed in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

probabilities. Data limitations do not allow us to exploit variation in priors for each of the three location alternatives, so we construct priors of facility quality at institutions in general (both public and private). While the DLHS-III is limited in data on pre-delivery beliefs, we nonetheless view our measures of priors to be noisy proxies of pre-delivery perceptions of facility quality. Reducing the mother's decision to a binary choice problem (institutional or home delivery), we estimate equation (5.2) by probit.

Table 7 shows results from regressions of institutional delivery on JSY being implemented and women's priors of facility quality. The magnitude of the marginal effects related to priors do not have a clear economic meaning, but their sign is revealing. In column 2 we see that a higher prior increases the likelihood of institutional delivery. This effect, however, is weakened when JSY exists in a woman's district. This is an interesting finding, which suggests that JSY induced those with low priors to deliver in medical facilities more so than those with high priors. Similar results are found in columns 3-4 with our second measure of priors. In column 6 we see that higher priors are associated with higher probabilities of institutional delivery, and that this effect is stronger for ineligible mothers who may be less resource constrained. One endogeneity concern with this specification is that JSY may affect women's priors even before they give birth. For example, simply knowing that a new public health program exists in one's district may raise one's perception of facility quality. To mitigate this concern, we re-estimate equation (5.2) on a sub-sample of women that gave birth either prior to JSY's introduction in their district or in the the month JSY was introduced itself. Since our measure of priors uses survey responses related to pre-natal care, we thus exclude women who received pre-natal care during JSY's existence in their district. Columns 7-8 show results on this sub-sample. While marginal effects are slightly different because of the selected sample, the direction of the effects remains.

The results in Tables 4-7 show a large and significant impact of JSY on institutional deliveries. Including state and month fixed effects help limit omitted variable bias from unobserved factors varying across regions and time. Analysis in section 5.3.2 shows that compositional changes in the attributes of mothers are uncorrelated with the timing of JSY implementation, and that district-level characteristics cannot explain the within-state variation in program adoption. These facts make it unlikely that some factor other than JSY is driving these results. Nevertheless, in Appendix section 8.7 we detail two alternative explanations for our findings. These relate to changes in the quality of care for home deliveries that may have induced women to start utilizing the formal health sector, and changes in the availability of medical facilities due to supply-side investments under the NRHM. We do not find, however, that these alternative stories can explain the patterns we see in the data.

Table 7:
Effects of JSY on Institutional Delivery, Including Priors on Quality

	All Births						Excludes Births post Initial JSY Month	
	Prior: Measure 1		Prior: Measure 2				Prior: Measure 2	
Covariates	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
JSY Implemented	0.038***	0.043***	0.038***	0.042***	-0.023*	-0.022*	0.056***	0.057***
	(0.011)	(0.010)	(0.011)	(0.010)	(0.013)	(0.013)	(0.010)	(0.010)
Prior		0.298***		0.186***		0.188***		0.172***
		(0.004)		(0.003)		(0.004)		(0.003)
JSY Implemented × Prior		-0.021***		-0.030***		0.008		-0.034***
		(0.005)		(0.004)		(0.007)		(0.007)
Eligible					-0.014*	-0.015**		
					(0.007)	(0.007)		
JSY Implemented × Eligible					0.094***	0.092***		
					(0.011)	(0.012)		
Eligible × Prior						-0.010**		
						(0.005)		
JSY Imp. × Eligible × Prior						-0.039***		
						(0.009)		
Obs.	186,902	186,902	186,660	186,660	186,660	186,660	131,442	131442
Includes HH Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month and State Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Estimates by probit. Columns 1-6 include all mothers. Columns 7-8 includes only those who gave birth prior to JSY, or who delivered in the month JSY began (*i.e.* excludes births in JSY districts occurring more than 1 month after JSY began). The dependent variable is an indicator for institutional delivery. Individual and household characteristics include: dummies for SC, ST, BPL status, having insurance, and rural/urban status; a set of dummies for wealth quintiles; mother's age at birth; distance to facilities; and years of education of the household head. Regressions include population sampling weights. Coefficients are marginal effects and robust standard errors, clustered at the district level, are listed in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

6.2 Effects on Future Use of Facilities

In addition to the short-run program effects of increasing institutional delivery, the extent to which financial incentives for health can impact long-term behavior is an open question. Using equation (5.3) we estimate the effect of exposure to public medical facilities during one's most recent childbirth on later treatment of children, conditional on a child being ill. Table 8 shows marginal effects for a sample including any child of the mother, *i.e.* the most recently born child for which we have delivery location data as well as any older child. In column 1 we run an uninstrumented probit regression of formal treatment on exposure and find that exposure leads to an increased likelihood of treatment for future illness by 2.1 percentage points. Columns 2-6 instrument for exposure with the existence of JSY in a mother's district at the time of childbirth. The two-stage least squares estimate of future treatment on previous exposure is insignificant, but with binary variables for the outcome, treatment, and instrument, two-stage least squares is not preferred. The bivariate probit estimate in column 3 implies exposure raises the probability of treating a sick child in the future by 6.8 percentage points (out of a mean treatment rate of 71.9 percent), which is significant at the 90 percent confidence level. This effect is larger than in column 1, indicat-

Table 8:
Effects of Facility Use on Future Treatment of Sick Children

	Probit	2SLS	Bivariate Probit			
Covariates	(1)	(2)	(3)	(4)	(5)	(6)
Exposed	0.021***	0.050	0.068*	0.067*	0.055**	0.026***
	(0.006)	(0.120)	(0.036)	(0.038)	(0.025)	(0.008)
Illness is Severe				0.167***	0.160***	
				(0.004)	(0.018)	
Age of Child (mths.)				-0.000		-0.004*
				(0.001)		(0.002)
Exposed × Illness is Severe					0.028	
					(0.073)	
Exposed × Age of Child (mths.)						0.014**
						(0.007)
Obs.	39,995	39,995	39,995	39,689	39,693	39,687
Instrument for Exposed	No	Yes	Yes	Yes	Yes	Yes
Includes Household Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Month and State Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Estimates in columns 3-6 by a fully interacted system of equations and MLE assuming bivariate normality of error terms. First stage dependent variable: "Exposed" (dummy for using public facility for childbirth); instrument: existence of JSY at the time of most recent childbirth. Main equation dependent variable: dummy for receiving treatment conditional on being sick. Individual and household characteristics include: dummies for SC, ST, BPL, having insurance, and rural status; dummies for wealth quintiles; distance to facilities; mother's age; and years of education of the household head. Coefficients are marginal effects with robust standard errors listed in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

ing downward bias in the probit estimate which does not account for mothers' preferences or expectations. One explanation could be related to Prediction 3, which states that the probability of institutional birth increases with the probability of being sick in the future. If during pregnancy women had low expectations of needing to treat their children in the future, thus opting for home delivery, the probit estimate would underestimate the effect of exposure if mothers later sought care for unexpected medical needs. In column 4 we control for the child's age (which also partially controls for length of time since delivery), as well as include an indicator variable for whether or not the illness was self-proclaimed as severe. We find similar results with these controls. In column 5 we interact exposure with illness severity. While the point estimate on exposure falls slightly, it is measured with more precision, though there are no differential effects by severity. Column 6 interacts exposure with age, indicating that the positive effect of exposure on treatment is increasing with the age of the child.

We further investigate how exposure to public medical facilities at the time of childbirth influences the type of treatment facility chosen for future illnesses. Table 9 shows results separately for public and private facilities where we regress whether or not a child was treated in a public (private) facility on the same instrumented measure of exposure. Exposure to public facilities is found to significantly increase the probability of going to a public facility again, but reduce the probability of later seeking care for a sick child at a private facility.

Table 9:
Effects on Future Treatment of Sick Children, by Future Treatment Location

	Panel A - Treatment in a Public Facility					
	Probit	2SLS	Bivariate Probit			
Covariates	(1)	(2)	(3)	(4)	(5)	(6)
Exposed	0.091***	0.303	0.053	0.054	0.075***	0.093***
	(0.004)	(0.262)	(0.036)	(0.036)	(0.020)	(0.007)
Illness is Severe				0.035***	0.031**	
				(0.004)	(0.015)	
Age of Child (months)				-0.000		-0.000
				(0.001)		(0.001)
Exposed × Illness is Severe					0.013	
					(0.058)	
Exposed × Age of Child (months)						-0.000
						(0.002)
Obs.	39,989	39,993	39,993	39,685	39,689	39,989
	Panel B - Treatment in a Private Facility					
	Probit	2SLS	Bivariate Probit			
	(7)	(8)	(9)	(10)	(11)	(12)
Exposed	-0.075***	-0.479	-0.111**	-0.114***	0.008	-0.062***
	(0.006)	(0.326)	(0.043)	(0.042)	(0.027)	(0.010)
Illness is Severe				0.107***	0.112***	
				(0.005)	(0.020)	
Age of Child (months)				-0.001**		-0.001
				(0.001)		(0.001)
Exposed × Illness is Severe					-0.016	
					(0.081)	
Exposed × Age of Child (months)						-0.003
						(0.003)
Obs.	39,993	39,993	39,993	39,686	39,690	39,989
Instrument for Exposed	No	Yes	Yes	Yes	Yes	Yes
Includes Household Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Estimates in columns 3-6 and 9-12 by a fully interacted system of equations and MLE assuming bivariate normality of error terms. First stage dependent variable: "Exposed" (dummy for using public facility for childbirth); instrument: existence of JSY at the time of most recent childbirth. Main equation dependent variable: dummy for treatment location conditional on being sick. Individual and household characteristics include: dummies for SC, ST, BPL, having insurance, and rural status; dummies for wealth quintiles; distance to facilities; mother's age; and years of education of the household head. Coefficients are marginal effects with robust standard errors listed in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

This type of substitution is consistent with both learning about facility quality (if women revise upward their priors on public facility quality) and paying one-time experience costs. We explore the prevalence of these mechanisms below.

The use of facilities in one period may also affect women's decisions to seek treatment for themselves in the future. Table 10 shows results from regressions of whether or not a woman sought treatment at a medical facility for a recent condition on exposure to public medical facilities at the time of childbirth, conditional on being ill. Results from an uninstrumented probit regression in column 1 reveal that exposure increases the probability of future

Table 10:
Effects on Future Treatment of Women's Personal Illnesses

	Probit	2SLS	Bivariate Probit			
Covariates	(1)	(2)	(3)	(4)	(5)	(6)
Exposed	0.019***	0.093	-0.026	-0.017	0.007	-0.013
	(0.006)	(0.236)	(0.044)	(0.044)	(0.009)	(0.010)
Number of Medical Problems				0.044***	0.045***	
				(0.002)	(0.007)	
Months Since Last Birth				0.007***		-0.002
				(0.002)		(0.009)
Exposed × No. of Medical Problems					-0.005	
					(0.027)	
Exposed × Months Since Last Birth						0.012
						(0.028)
Obs.	45,354	45,353	45,354	43,296	45,356	43,298
Instrument for Exposed	No	Yes	Yes	Yes	Yes	Yes
Includes Household Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Estimates in columns 3-6 by a fully interacted system of equations and MLE assuming bivariate normality of error terms. First stage dependent variable: "Exposed" (dummy for using public facility for childbirth); instrument: existence of JSY at the time of most recent childbirth. Main equation dependent variable: dummy for receiving treatment conditional on being sick. Individual and household characteristics include: dummies for SC, ST, BPL, having insurance, and rural status; dummies for wealth quintiles; distance to facilities; mother's age; and household head's years of education. Coefficients are marginal effects with robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

treatment by 1.9 percentage points. Columns 2-6 instrument for exposure by the existence of JSY at the time of childbirth. We do not find, however, that our measure of exposure has predictive power in these specifications. More medical problems is positively associated with seeking treatment, but institutional birth has a small and insignificant effect on a woman's propensity to visit a facility conditional on being ill once we instrument for exposure. Measures of recent illness for children relate to fevers and coughs, whereas for women they include potentially more chronic ailments. Dror *et. al* (2008) find in Bihar, Maharashtra, and Tamil Nadu that out-of-pocket expenses for treatment of chronic ailments are 22.5 percent higher than for acute illnesses (which includes fevers and coughs), and that payments made to treat adults aged 16 to 55 are 6.7 percent higher than treatments for children aged 5 to 15. If the importance of costs to expected utility is sufficiently high, these facts are consistent with our results; prior facility usage impacts future usage, but only for relatively low cost needs.

Recall from Table 8 that we found downward bias in the probability of using a medical facility for children's illnesses when we do not instrument for exposure, possibly due to mothers' low expectations of future facility needs for children. This is in contrast to the upward bias in Table 10 for women. One explanation for this divergence in effects relates to the differences in illness types. Chronic ailments are more commonly associated with repeated need for medical care, thus those with such conditions likely have relatively high expectations for later being in a health state that requires choosing to visit a medical facility. Acute illness, by contrast, occur more abruptly, and so women likely have relatively lower expectations regarding needing to visit a health facility in the future for such conditions. Since the illnesses we examine for women are more chronic, following Prediction 3 high expectations for future facility needs, coupled with preferences over health in general and facility types, would then lead to positive bias in an uninstrumented regression examining women's treatment of themselves (since those women positively select into first period institutional delivery).

Having found that using a public medical facilities increases the probability of a mother seeking care for her child later in life by 6.8 percentage points, we examine which mechanisms may be driving this result. Prediction 4 in conjunction with Result 1 state: first, that if women maintain or reduce their perceptions of quality after using a facility, yet are more likely to seek facility treatment later in life, then having paid one-time experience costs increases the relative utility and probability of facility treatment; and second, if women revise down their beliefs over quality, and are less likely to utilize facilities in the future, then learning about clinician quality dominates any effect of paying experience costs. Comparing signals to priors we identify women as having revised up, down, or not at all their beliefs with respect to facility quality. Those that do not utilize institutional delivery do not receive a signal and perform no updating.

Table 11 shows results from estimation of equation (5.4) of future treatment of children, conditional on being sick, on institutional delivery and belief revision using both measures of priors. The omitted category is home births. In the uninstrumented regressions we find positive and statistically significant increases in the probability of future treatment for those who had an institutional delivery regardless of the direction of belief revision. In columns 2 and 5 we instrument for institutional delivery and find that women who delivered in a formal medical facility and revise up their beliefs over facility quality are 8.1 and 10.3 percentage points, respectively, more likely to seek formal treatment for their sick children relative to women who delivered at home, while those who did not update their beliefs are still 8.2 and 9.2 percentage points, respectively, more likely to seek treatment. Across both prior measures there is an insignificant effect of institutional delivery for those that revised down expectations over quality. Marginal effects reduce in magnitude slightly when controlling for illness severity and time since childbirth in columns 3 and 6, though the difference in point estimates between revising down and revising up, and revising down and no revision, are statistically significant.

Referring to inequality (4.4), these findings suggest that both paying one-time experience costs and learning about clinician quality are present. Those who revise down beliefs over quality are not less likely to seek treatment for children, and those that do not update

Table 11:
Effects of Institutional Delivery and Belief Revision on Future Treatment of Sick Children

	Prior: Measure 1			Prior: Measure 2		
Covariates	(1)	(2)	(3)	(4)	(5)	(6)
Institutional Delivery × Revise Down	0.019**	0.019	0.021	0.011	-0.001	-0.016
	(0.008)	(0.044)	(0.046)	(0.009)	(0.046)	(0.047)
Institutional Delivery × No Update	0.027***	0.082*	0.074	0.048***	0.092**	0.079*
	(0.009)	(0.045)	(0.047)	(0.009)	(0.045)	(0.045)
Institutional Delivery × Revise Up	0.056***	0.081*	0.066	0.059***	0.103**	0.070
	(0.010)	(0.048)	(0.051)	(0.010)	(0.046)	(0.048)
Months Since Last Birth			0.000			-0.000
			(0.001)			(0.001)
Illness is Severe			0.166***			0.164***
			(0.005)			(0.005)
Obs.	36,300	36,305	36,044	30,995	30,995	30,783
Instrument for Institutional Delivery	No	Yes	Yes	No	Yes	Yes
Includes Household Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Month and State Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
p-value for Test of Coefficient Equality:						
Revise Down and No Update	0.636	0.003***	0.011**	0.002***	0.000***	0.001***
Revise Down and Revise Up	0.002***	0.006***	0.042**	0.000***	0.000***	0.001***
No Update and Revise Up	0.011**	0.980	0.756	0.403	0.660	0.703

Estimates in columns 1 and 4 by probit; all others by a fully interacted system of equations and MLE assuming bivariate normality of error terms. Parameter restrictions are imposed on all variables except for interaction terms such that coefficients of control variables are equal across equations. Institutional delivery is instrumented with the existence of JSY at the time of most recent childbirth. Main equation dependent variable: dummy for receiving treatment conditional on being sick. Individual and household characteristics include: dummies for SC, ST, BPL status, having insurance, and rural/urban status; a set of dummies for wealth quintiles; mother's age; distance to facilities; and years of education of the household head. Coefficients are marginal effects with robust standard errors listed in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

are significantly more likely. Thus regardless of one's perception over quality, the probability of future use is (weakly) higher for everyone that utilized institutional delivery, implying that women internalize payment of one-time experience costs after facility use. Further, the magnitude of the effect for those that weakly revise up beliefs over quality is significantly larger than for those that revising down in all of the instrumented specifications. With the full set of controls in columns 3 and 6, the 4.5 and 8.6 percentage point differences, respectively, between revising up and revising down are statistically different at the 95 percent confidence level (p-value=0.042 and 0.001). Since women who have relatively high signals have a higher probability of utilizing institutional treatment than those who have relatively low signals over facility quality, learning about quality also appears to impact health-seeking behavior.

While individuals may have internalized paying one-time experience costs after institutional delivery, it is true that many of these women would have visited health care facilities earlier in their lives, and thus already paid these costs in the past. In this case, institutional delivery should not have as strong of an effect on their behavior. Further, those who visited facilities in the past should have a better defined belief over facility quality, lessening the importance of one's recent visit for childbirth for their belief formation. We therefore compare the effect of institutional delivery on future treatment probabilities for those that had previously visited a health facility and those that did not. We use data on pre-natal care visits or other facility visits during pregnancy to define previous experience. The first half of Table 12 shows that institutional delivery raises the probability of future treatment of sick children by 8.4 percentage points for those that had not been to a facility before. No differential effect exists, however, for those with previous facility experience.

Since medical care is costly, it is possible that persistence in facility treatment also occurs due to an income effect. Illnesses we analyze in the second period occur on average nearly 20 months after childbirth, though we test for an income effect by comparing women who gave birth before and after cash incentives were increased in low states in November 2006. For an income effect to be present, those who delivered after late 2006 should be more likely to finance future medical needs at institutions. The second half of Table 12 compares future treatment probabilities for those giving birth before and after late 2006. We find the marginal effects of institutional delivery on future treatment are no different for the early and late birth cohorts. This casts doubt on income effects being responsible for the results seen in Tables 8-11.

Table 12:
Experience Costs and Income Effects (Treatment of Children)

	Experience Costs		Income Effects	
Covariates	Previously Visited Facility	Didn't Previously Visit Facility	Pre-Nov. 2006	Post-Nov. 2006
Institutional Delivery	0.007	0.084**	0.040	0.030
	(0.038)	(0.042)	(0.051)	(0.029)
Months Since Last Birth	-0.000	-0.000	0.007***	0.003**
	(0.001)	(0.001)	(0.002)	(0.002)
Illness is Severe	0.163***	0.177***	0.178***	0.092***
	(0.004)	(0.005)	(0.005)	(0.036)
Obs.	39,682		29,207	
Instrument for Institutional Delivery	Yes		Yes	
Includes Household Characteristics	Yes		Yes	
Month Fixed Effects	Yes		No	
State Fixed Effects	Yes		Yes	
p-value for Test of Coefficient Equality:				
Previously and Didn't Previously Visit	.000***			
Pre Nov. 2006 and Post Nov. 2006			0.361	

Estimates by a fully interacted system of equations and MLE assuming bivariate normality of error terms. Parameter restrictions are imposed on all variables except for interaction terms such that coefficients of control variables are equal across equations. Institutional delivery is instrumented with JSY's existence at the time of most recent childbirth. Main equation dependent variable: dummy for receiving treatment conditional on being sick. Individual and household characteristics include: dummies for SC, ST, BPL, having insurance, and rural status; dummies for wealth quintiles; distance to facilities; mother's age; and household head's years of education. Coefficients are marginal effects with robust standard errors listed in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

An alternative interpretation of these results relates to expectations of admission probabilities. By definition, anyone who delivered in a formal medical facility was admitted by facility staff and was not refused to be seen. In many Indian contexts some people, particularly the poor and lower caste groups, are apprehensive about utilizing formal institutions for fear of being discriminated against. Having a successful birth in a facility may simply make these women revise up their expectations about being admitted again, increasing the probability they opt for formal treatment in the future. If our measure of signals and priors incorporates this aspect of expectations then our interpretation of the results holds. Otherwise, what we attribute to paying one-time experience costs may in part be this alternative aspect of learning. Nonetheless, we take these results as evidence that institutional delivery induced by JSY has lasting positive effects on women's use of formal medical care in India.

7 Conclusion

Understanding the long-term impacts of conditional cash transfer programs is of particular importance to policymakers and researchers. While financial incentives have been shown to have strong short-term effects on health, the welfare benefits of conditional cash transfer programs are enhanced if adopted behaviors persist when subsidies end. We find in the case of JSY that subsidized use of institutional delivery affects unsubsidized behaviors; women who give birth in formal medical facilities are more likely to seek care in formal facilities again when their children are ill later in life.

We explore three potential mechanisms for why facility choice in one period may affect future choices, including paying one-time fixed costs of facility use, learning about quality, and income effects. Our empirical results suggest that in this context persistence in health-seeking behavior is driven both by paying one-time experience costs and through learning about facility quality. Finding that any mechanism is present is encouraging if it means that people are more likely to participate in the formal health care sector, and our results indicate that both demand- and supply-side initiatives can improve health care utilization: subsidizing fixed costs makes it more affordable for a household to utilize a product or service again, but households will also respond to the relative quality of health facilities while making treatment decisions.

We do not find that women are more likely to seek formal treatment for their own ailments after previous facility use. If unequal expenses for treating sick children and adults are leading to these differential effects, then short-term subsidies for health may only have long-term impacts in select contexts and for relatively inexpensive services.

Corruption, political disagreements, and budgetary bottlenecks often impede swift program adoption at the local level. We find that JSY did not become operational on average at the district level for nearly two years after the Central government formally launched the initiative. Awareness of why these delays occur may help policymakers design better program rollout. In this setting, however, apart from a small but significant positive correlation between the presence of female politicians in a district and program adoption, we show the timing of JSY's implementation within states to be orthogonal to many factors that may also influence health care utilization.

One important limitation to this paper is that that in the DLHS-III we only observe a birth outcome and then illnesses in the three months preceding a woman's interview, but not a complete history of all health facility visits and illness episodes. Individuals may gather information from a larger set of outcomes and experiences which we do not observe. Further, the process of learning about facility and clinician quality is not instantaneous and households may not learn much after only one provider visit. Thus observing a more complete panel of health episodes along with treatment choices would strengthen our ability to examine effects of learning on health-seeking behavior. Previous work has also highlighted effects of social learning in health care and other contexts. Signals may not be entirely private information, but individuals likely learn about heath care facilities from members of their social network. Examining whether social learning is present in this context is one avenue for future research which we plan to explore.

References

[1] Aizer, Anna, and Janet Currie (2004). "Networks or neighborhoods? Correlations in the use of publicly-funded maternity care in California," *Journal of Public Economics*, 88: 2573-85.

[2] Ansolabehere, Stephen, and James M. Snyder, Jr., (2006). "Party Control of State Government and the Distribution of Public Expenditures," *Scandinavian Journal of Economics*, 108(4): 547-569.

[3] Alesina, Alberto, Reza Baqir, and William Easterly, (1999). "Public Goods and Ethnic Divisions," *The Quarterly Journal of Economics*, 114(4): 1243-1284.

[4] Babcock, Philip, and John Hartman, (2010). "Networks and Workouts: Treatment Size and Status Specific Peer Effects in a Randomized Field Experiment, NBER Working Paper No. 16581.

[5] Bai, Jushan, (1994). "Least Squares Estimation of a Shift in Linear Processes," *Journal of Time Series Analysis*, 15: 453-472.

[6] Banerjee, Abhijit, Lakshmi Iyer, and Rohini Somanathan, (2005). "History, Social Divisions and Public Goods in Rural India," *Journal of the European Economic Association*, 3(2-3): 639647.

[7] Barham, Tania, Karen Macours, and John Maluccio, (2013). "More Schooling and More Learning? Effects of a Three-Year Conditional Cash Transfer Program in Nicaragua after 10 Years," IDB Working Paper Series No. IDB-WP-432.

[8] Becker, Gary, and Kevin M. Murphy, (1988). "A Theory of Rational Addiction," *The Journal of Political Economy*, 96(4): 675-700.

[9] Center for Budget and Governance Accountability (CBGA), UNICEF, (2011). "National Rural Health Mission (NRHM)," *Budgeting for Change Series*, 1-26.

[10] Chattopadhyay, Raghabendra, and Esther Duflo, (2004). "Women as policy makers: Evidence from a Randomized Policy Experiment in India," *Econometrica*, 72(5): 1409-1443.

[11] Charness, Gary, and Uri Gneezy, (2009)."Incentives to Exercise," *Econometrica*, 77(3): 909-31.

[12] Chaudhury, Nazmul, and Jeffrey Hammer, (2005). "Ghost Doctors: Absenteeism in Bangladeshi Health Facilities," *World Bank Economic Review*, 18(3): 423-41.

[13] Chaudhury, Nazmul, Jeffrey Hammer, Michael Kremer, Karthik Muralidharan and F. Halsey Rogers (2004). "Missing in Action: Teacher and Health Worker Absence in Developing Countries," *Journal of Economic Perspectives*, 20(1): 91-116.

[14] Clots-Figueras, Irma, (2011). "Women in Politics: Evidence from the Indian States," *Journal of Public Economics*, 95: 664-690.

[15] Comptroller and Auditor General of India, Government of India, Government of Uttarakhand, (2008). "Performance Audit of National Rural Health Mission (NRHM)."

[16] Dagur, Vikas, Katherine Senauer, and Kimberly Switlick-Prose, (2010). "Paying for Performance: The Janani Suraksha Yojana Program in India," USAID, Health Systems 20/20.

[17] Das, Jishnu, and Jeffrey Hammer, (2004). "Which Doctor? Combining Vignettes and Item Response to Measure Clinical Competence," *Journal of Development Economics*, 78: 348-83.

[18] Das, Jishnu, Alaka Holla, Michael Kremer, and Karthik Muralidharan, (2013). "Quality and Accountability in Health: Audit Evidence From Primary Care Providers," Working Paper.

[19] Debnath, Sisir, (2013). "Improving Maternal Health with Incentives to Mothers vs. Health Workers: Evidence from India," Working Paper.

[20] Dongre, Ambrish, (2012). "Can Conditional Cash Transfers Impact Institutional Deliveries? Evidence from Janani Suraksha Yojana in India," Working Paper.

[21] Dupas, Pascaline, (2014). "Short-run Subsidies and Long-Run Adoption of New Health Products: Evidence from a Field Experiment," *Econometrica*, 82(1): 197-228.

[22] Dror, David M., Olga van Putten-Rademaker, and Ruth Koren, (2008). "Cost of illness: Evidence from a study in five resource-poor locations in India," *The Indian Journal of Medical Research*, 127(4): 347-61.

[23] Epple, Dennis, (1999). "Estimating Equilibrium Models of Local Jurisdictions," *The Journal of Political Economy*, 107(4): 645-81.

[24] Gertler, Paul, and Christel Vermeersch, (2013). "Using Performance Incentives to Improve Medical Care Productivity and Health Outcomes," NBER Working Paper 19046.

[25] Gneezy, Uri, Stephan Meier, and Pedro Rey-Biel, (2011). "When and Why Incentives (Dont) Work to Modify Behavior," *Journal of Economic Perspectives*, 25(4): 1-21.

[26] Hansen, Bruce E, (1999). "Threshold effects in non-dynamic panels: Estimation, testing, and inference," *Journal of Econometrics*, 93: 345-368.

[27] Hansen, Bruce E, (2000). "Sample Splitting and Threshold Estimation," *Econometrica*, 68(3): 575-603.

[28] India National Congress (INC), (2009). "Lok Sabha Elections 2009 Manifesto of the Indian National Congress."

[29] Lim, Stephen S., Lalit Dandona, Joseph A. Hoisington, Spencer L. James, Margaret C. Hogan, and Emmanuela Gakidou, (2010). "India's Janani Suraksha Yojana, a conditional cash transfer programme to increase births in health facilities: an impact evaluation," *The Lancet*, 375: 2009-23.

[30] Leonard, Kenneth L., (2007). "Learning in Health Care: Evidence of Learning about Clinician Quality in Tanzania," *Economic Development and Cultural Change*, 55(3): 531-55.

[31] Leonard, Kenneth L., (2009). "Improving health outcomes by choosing better doctors: Evidence of social learning from rural Tanzania," Working Paper.

[32] Leonard, Kenneth L., and Melkiory C. Masatu, (2010)."Using the Hawthorne Effect to examine the gap between a doctors best possible practice and actual practice," *Journal of Development Economics*, 93(2): 226-34.

[33] Mazumdar, Sumit, Anne Mills, and Tomothy Powell-Jackson, (2011). "Financial Incentives in Health: New Evidence from India's Janani Suraksha Yojana," Working Paper.

[34] MaCurdy, Thomas, Bryan Keating, Sriniketh Nagavarapu, and David Glick, (2014). "Profiling the Plight of Disconnected Youth in America," Working Paper.

[35] McFadden, Daniel, (1978). "Modelling the choice of residential location," in Karlqvist, A., Lundqvist, L., Snickars, F. and Weibull, J. (Eds.) *Spatial Interaction Theory and Residential Location*, North-Holland: Amsterdam, 75-96.

[36] Miguel, Edward, and Mary Kay Gugerty, (2005). "Ethnic Diversity, Social Sanctions and Public Goods in Kenya," *Journal of Public Economics*, 89: 2325-68.

[37] Ministry of Health and Family Welfare, Government of India, (2014). "Institutional setup under NRHM: Composition of DHM & DHS," http://nrhm.gov.in.

[38] Ministry of Health and Family Welfare, Government of India, (2005). "National Rural Health Mission: Meeting people's health needs in rural areas, Framework for Implementation 2005-2012."

[39] Munshi, Kaivan, and Mark Rosenzweig, (2013). "Networks, Commitment, and Competence: Caste in Indian Local Politics," Working Paper.

[40] Niehaus, Paul, Antonia Atanassova, Marianne Bertrand, and Sendhil Mullainathan, (2013). "Targeting with Agents," *American Economic Journal: Economic Policy*, 5(1): 206-38.

[41] Okeke, Edward, and A.V. Chari, (2013). "Can Institutional Deliveries Reduce Newborn Mortality? Evidence from Rwanda," Working Paper.

[42] Powell-Jackson, Timothy, and Kara Hanson, (2012). "Financial incentives for maternal health: Impact of a national programme in Nepal," *Journal of Health Economics*, 31: 271-84.

[43] Roodman, David, (2011). "Fitting fully observed recursive mixed-process models with cmp," *The Stata Journal*, 11(2): 159-206.

[44] Roy, Debjit, Sahil Narang, and K.V. Ramani, (2013). "Planning the Activities of Doctors in a Teaching Hospital," *Indian Institute of Management Ahmedabad Working Paper*, No WP2013-06-05.

[45] Save the Children, (2013). "Surviving the First Day: State of the World's Mothers 2013," Save the Children Federation, Inc.

[46] Shleifer, Andrei, and Robert W. Vishny, (1994). "Politicians and Firms," *The Quarterly Journal of Economics*, 109(4): 995-1025.

[47] Tiebout, Charles M., (1956). "A Pure Theory of Local Expenditures," *The Journal of Political Economy*, 416-24.

[48] United Nations Population Fund —India, (2009). "Concurrent assessment of Janani Suraksha Yojana (JSY) in selected states: Bihar, Madhya Pradesh, Orissa, Rajasthan, Uttar Pradesh," UNFPA: New Delhi.

[49] Volpp, Kevin G., Leslie John, Andrea Troxel, Laurie Norton, Jennifer Fassbender, and George Loewenstein, (2008). "Financial Incentive-Based Approaches for Weight Loss: A Randomized Trial." *Journal of American Medical Association*, 300(22): 2631-37.

[50] Williams, H., (1977). "On the formation of travel demand models and economic evaluation measures of user benefits," *Environment and Planning A*, 9: 285-344.

8 Appendix

8.1 Comparative Statics on Delivery Location Probabilities

In section 4.2 we show the probability of choosing alternative j for childbirth equals:

$$\Pr(w^1_{ijd}=1)=\frac{e^{\left(\mathrm{v}^1_{ijd}+\delta\pi_{id}\ln\left[\sum_{k=1}^{3}e^{(\mathrm{v}^2_{ikd}(w^1_{id}))}\right]\right)}}{\sum_{j=1}^{3}e^{\left(\mathrm{v}^1_{ijd}+\delta\pi_{id}\ln\left[\sum_{k=1}^{3}e^{(\mathrm{v}^2_{ikd}(w^1_{id}))}\right]\right)}},$$

where $\mathrm{v}^t_{ijd}=\gamma^t_{id}\mu_{ijd}-c^t_{ijd}-\lambda^t_{jd}(w^{t-1}_{id})$. In section 4.3 we list a number of model predictions, and provide here the functional form of the derivatives given in these predictions. We show derivatives for $\frac{\partial\Pr(w^1_{id}=1)}{\partial(\cdot)}$ (change in probability of public delivery) only (and omit subscripts i and d for ease of exposition), though the derivatives for $j=\{2,3\}$ are calculated similarly.

Prediction 1.

$$\begin{aligned}\frac{\partial\Pr(w^1=1)}{\partial JSY}&=\frac{\mathbb{1}(eligible)\mathbb{1}(exist^1)e^{\mathrm{v}^1_1}\Big(\sum_{j=1}^{3}e^{\mathrm{v}^2_j(w^1=1)}\Big)^{\delta\pi}\Big[e^{\mathrm{v}^1_2}\Big(\sum_{j=1}^{3}e^{\mathrm{v}^2_j(w^1=2)}\Big)^{\delta\pi}+\Big(\sum_{j=1}^{3}e^{\mathrm{v}^2_j(w^1=3)}\Big)^{\delta\pi}\Big]}{\Big[\sum_{j=1}^{3}e^{\left(\mathrm{v}^1_j+\delta\pi\ln\left[\sum_{k=1}^{3}e^{(\mathrm{v}^2_k(w^1))}\right]\right)}\Big]^2}\\&>0\iff\mathbb{1}(eligible)=\mathbb{1}(exist^1)=1.\end{aligned}$$

Prediction 2.

$$\frac{\partial\Pr(w^1=1)}{\partial\mu_1}=\frac{\gamma^1e^{\mathrm{v}^1_1}\Big(\sum_{j=1}^{3}e^{\mathrm{v}^2_j(w^1=1)}\Big)^{\delta\pi}\Big[e^{\mathrm{v}^1_2}\Big(\sum_{j=1}^{3}e^{\mathrm{v}^2_j(w^1=2)}\Big)^{\delta\pi}+\Big(\sum_{j=1}^{3}e^{\mathrm{v}^2_j(w^1=3)}\Big)^{\delta\pi}\Big]}{\Big[\sum_{j=1}^{3}e^{\left(\mathrm{v}^1_j+\delta\pi\ln\left[\sum_{k=1}^{3}e^{(\mathrm{v}^2_k(w^1))}\right]\right)}\Big]^2}>0.$$

Prediction 3.

$$\begin{aligned}\frac{\partial\Pr(w^1=1)}{\partial\pi}&=\frac{\delta e^{\mathrm{v}^1_1}\Big(\sum_{j=1}^{3}e^{\mathrm{v}^2_j(w^1=1)}\Big)^{\delta\pi}}{\Big[\sum_{j=1}^{3}e^{\left(\mathrm{v}^1_j+\delta\pi\ln\left[\sum_{k=1}^{3}e^{(\mathrm{v}^2_k(w^1))}\right]\right)}\Big]^2}\times\\&\Big\{e^{\mathrm{v}^1_2}\Big(\sum_{j=1}^{3}e^{\mathrm{v}^2_j(w^1=2)}\Big)^{\delta\pi}\Big[\ln(e^{\mathrm{v}^2_1(w^1=1)}+e^{\mathrm{v}^2_2(w^1=1)}+1)-\ln(e^{\mathrm{v}^2_1(w^1=2)}+e^{\mathrm{v}^2_2(w^1=2)}+1)\Big]\\&+\Big(\sum_{j=1}^{3}e^{\mathrm{v}^2_j(w^1=3)}\Big)^{\delta\pi}\Big[\ln(e^{\mathrm{v}^2_1(w^1=1)}+e^{\mathrm{v}^2_2(w^1=1)}+1)-\ln(e^{\mathrm{v}^2_1(w^1=3)}+e^{\mathrm{v}^2_2(w^1=3)}+1)\Big]\Big\}\\&>0\iff\Big(\mathrm{v}^2_1(w^1=1)>\mathrm{v}^2_1(w^1=2)\Big)\text{ or }\Big(\mathrm{v}^2_2(w^1=1)>\mathrm{v}^2_2(w^1=2)\Big)\\&\quad\iff(\gamma^2\mu_1-c^2_1>\gamma^2\mu_1-c^2_1-\lambda^2_1)\text{ or }(\gamma^2\mu_2-c^2_2>\gamma^2\mu_2-c^2_2-\lambda^2_2)\\&\quad\iff\lambda^2_1>0\text{ or }\lambda^2_2>0.\end{aligned}$$

8.2 Specifics on Mean-Shift Estimation of District-Level Start Dates

We estimate the month JSY began in each of India's districts using a mean-shift model (Bai (1994); Munshi and Rosenzweig (2013)). Unlike Maximum Likelihood techniques to estimate a structural change-point, we apply least squares because it does not assume any underlying distribution of the error term and is computationally simple (Bai (1994)). For each district we allow the set of possible start dates to range from the month that the district's state officially constituted District Health Societies by approving the NRHM's Bylaws ($\tau = 0$, between May 2005 and March 2006) to the last month of birth history data for women in that district ($\tau = T$, between December 2007 to December 2008). The change-point is identified as the date which yields the largest mean-shift in receipt of JSY funds out of all possible dates. We test the null hypothesis of no structural change (no program exists) versus the alternative hypothesis that the program is present by estimating, separately for each district and each $\tau \in (0, T)$, the following equation:

$$y_{it} = \beta_0 + \beta_1 D_{i\tau} + \beta_2 (\textit{Post-Nov 2006})_{it} + \beta_3 Rural_{it} + \epsilon_{it}. \tag{8.1}$$

Here y_{it} is an indicator variable equal to 1 if woman i received a cash transfer for delivery in birth month t. The DLHS-III asked women whether they received any government financial assistance for delivery under JSY or any state-specific scheme. This wording about state-specific schemes was included since JSY took local language names in some states, but it also induced positive responses for people that received funds under the NMBS. As a result, 4.4 percent of women report receiving a transfer before April 2005. The monthly percent of women reporting this is constant, however, up through April 2005. Since there were no other maternal benefit schemes initiated at this time, any uptick in positive response rates to this question we attribute to JSY becoming operational. $D_{i\tau}$ is an indicator variable equal to 1 if birth month t is on or after the hypothetical JSY start date τ. $\textit{Post-Nov 2006}_{it}$ is a dummy variable equal to 1 if the birth month is on or after November 2006, where we condition on the early and late stages of the program to ensure that the start date is not selected due to eligibility and incentive changes at this time. This allows the change-point to be selected as the date with the largest shift in receipt of the cash transfer independent of changes to the program's configuration. $Rural_{it}$ is an indicator variable equal to 1 if the woman giving birth lives in a rural area of her district, which is added because JSY incentives differed by rural/urban status, thus helping avoid picking up regional compositional changes in births within a district over time. Finally, ϵ_{it} is a mean-zero, i.i.d. disturbance term.

Let $\underline{t}$ be the true district-level start date. To derive the least squares estimate of $\underline{t}$, $\hat{\underline{t}}$, we estimate equation (8.1) for all $\tau \in (0, T)$. $\underline{t}$ is then estimated by minimizing the residual sum of squares among all possible sample splits. That is, the least squares estimate of $\underline{t}$ is:

$$\hat{\underline{t}} = argmin_\tau \big[RSS(\tau) \big],$$

where $RSS(\tau)$ is the residual sum of squares when equation (8.1) is estimated with the assumed start date τ. Intuitively, equation (8.1) will best fit the data when $\underline{t} = \tau$.

To test the statistical significance of the estimated dates, consider the null hypothesis that any hypothetical start date is equal to the true start date against the alternative hypothesis that only the estimated start date is equal to the true start date. When the data generating process is consistent with equation (8.1), $\underline{t}$ is consistently estimated by $\hat{\underline{t}}$ (see Theorem 1 of Hansen (2000)). Following Hansen (1999), we test this null hypothesis against the alternative using a likelihood ratio test. The test statistic is calculated as follows:

$$LRT(\tau) = \frac{RSS(\tau) - RSS(\hat{\underline{t}})}{RSS(\hat{\underline{t}})} \times N.$$

The null hypothesis is rejected when the hypothetical start date is sufficiently far from the true program start date; that is, when $LRT(\tau)$ exceeds a critical value. Under the null the change-point cannot be identified, so the likelihood ratio test does not have a standard χ^2 distribution. Hansen (1999) derives the asymptotic distribution of $LRT(\tau)$ and corresponding critical values. Mechanically, $LRT(\tau) = 0$ when $\tau = \hat{\underline{t}}$. If the change-point is estimated precisely, $LRT(\tau)$ will increase quickly as the distance between τ and $\hat{\underline{t}}$ increases. The range of hypothetical start dates close to the estimated start date $\hat{\underline{t}}$ for which $LRT(\tau)$ is less than the 5 (10) percent critical value therefore defines the 95 (90) percent confidence interval for the district-level start date.

Figure A2 plots the mean $LRT(\tau)$ across all districts for each hypothetical district-level program start date within two years of the chosen start date. The value 0 on the horizontal axis represents the month that corresponds to $\hat{\underline{t}}$, and positive (negative) values represent the number of months after (before) that date. The mean $LRT(\tau)$ decreases sharply when the hypothetical start date approaches 0 from either side. The horizontal lines at 7.35 and 5.94 correspond to the 5 and 10 percent critical values, respectively, which allows us to place statistical bounds on the average estimated start date. Using a 95 percent confidence interval these bounds are [-3,2], while with a 90 percent confidence interval they are [-2,1]. If we weight the mean $LRT(\tau)$ by the number of births in each district the bounds become even more precise; [-2,2] and [-1,1] for 95 percent and 90 confidence intervals, respectively. Thus, on average across all districts the structural break is relatively well estimated.

8.3 Mean-Shift in Institutional Delivery and Composition of Mothers

For results from the estimated start dates to be consistent with the story that districts implemented JSY at the estimated change-point date, the percent of women choosing institutional births should also increase discontinuously at these dates. As noted above, low states experience a more noticeable increase in institutional births in the aggregate relative to high states. Nonetheless, both state types experience a rise in benefit recipients. This indicates that many women in high performing states who began receiving benefits were the types of women who would have chosen institutional delivery in the absence of JSY, but began receiving benefits because they met the eligibility criteria. If the number of these "always takers" dominate the number of "compliers," the patterns seen in the data will prevail.

We re-estimate equation (8.1) now with y_{it} as an indicator variable equal to 1 if mother i delivers her child in either a public or private facility at time t, and equal to 0 if the delivery occurs at home.[22] We run a separate regression for each district and for all $\tau \in (0, T)$. We calculate a likelihood ratio statistic for the τ-ith regression where $\underline{\hat{t}}$ is the same month as was estimated as the change-point month from (8.1). That is, we hold fixed the estimated JSY start date from before, and calculate the test statistic for each month relative to that date. Appendix Figure A3 shows the average test statistic across districts by state type. As expected the values are small and insignificant for high performing states. While receipt of JSY benefits increased in these states, institutional deliveries did not. However, the test statistic does become significantly different from zero for low performing states, although $LRT(\tau)$ does not decline as steeply as the relative start date approaches zero relative to Figure A2. Changes in program benefit receipts would have begun prior to an increase in institutional deliveries because "always takers" began receiving benefits as soon as the program commenced. On the other hand, it would take some time for those who were encouraged to utilize health facilities for delivery to start doing so, particularly since it would take time for women to learn about JSY. Thus any change in institutional delivery rates would be more gradual than benefit receipt rates, resulting is the bounds placed on significant values of $LRT(\tau)$ with respect to institutional delivery to be wider.

We also verify that the rise in receipt of the cash transfer is not driven by changes in the composition of mothers giving birth. To alleviate this concern, we re-estimate equation (8.1), but now with y_{it} equal to eight different variables related to mothers' socio-economic characteristics.[23] These characteristics include: years of education of the household head; mother's age at birth; indicator variables equal to 1 if any member of the household has medical insurance, the household lives in a rural locality, the household is a member of a scheduled

[22]The indicator variables for *Post-Nov 2006* and *Rural* are excluded from this estimation.
[23]The indicator variables for *Post-Nov 2006* and *Rural* are excluded from this estimation.

caste, scheduled tribe, or has BPL status; and the DLHS-III wealth index score. We run a separate set of regressions for each of these characteristics and for each district for all $\tau \in (0, T)$, calculating a likelihood ratio statistic for the τ-ith regression where $\underline{\hat{t}}$ is the same month as was estimated as the change-point month. Appendix Figure A4 depicts the district average likelihood ratio test statistic for each of these dependent variables. The average test statistics increase only slightly as the relative break month increases or decreases from zero, and they do not become significantly different from zero for any of the characteristics. This is in contrast to Figure A2 where receipt of cash transfers changed discontinuously at the estimated JSY start date. We conclude that underlying compositional change in the types of women giving birth are not driving results from the mean-shift model.

8.4 Insignificance of Some Estimated District-Level Start Dates

Figure A2, which plots the mean $LRT(\tau)$ across all districts, shows that estimated JSY start dates are on average estimated relatively precisely. This is not the case, however, for all districts individually. Using a 90 percent confidence interval 197 out of 581 districts (33.9 percent) do not see a statistically significant change in the percent of women receiving maternal delivery benefits over time (*i.e.*, the $LRT(\tau)$ for these districts are always below the 90 percent confidence bandwidth). Three plausible explanations for this are: (1) the program truly was not implemented in these districts; (2) these districts are small and so even moderate-sized changes in receipt percentages over time will not be statistically significant changes; or (3) the program was implemented but women did not receive benefits due to poor management of funds or lack of knowledge by health personnel.

The first possible reason does not seem to hold. District hospitals, community health centers (CHCs), and primary health centers (PHCs) were asked in the DLHS-III how many women were beneficiaries under JSY in the last month.[24] Only 2 of these 197 districts did not have any reported beneficiaries in the month prior to being interviewed. The second reason is also unlikely. These 197 districts recorded an average of 323.5 births per district from 2004 to 2007 in the DLHS-III, while the remaining 384 districts averaged 347.3 births (difference in means p-value=0.060). However, this difference over the course of 4 years corresponds to a monthly difference of only approximately 0.5 births. It is thus unlikely that such a small deviation is driving the lack of significance of the $LRT(\tau)$ in these districts.

[24] These are the principle public facilities a women would utilize to avail JSY benefits. India's public health system is comprised of rural-based sub-centers, primary health centers (PHCs), community health centers (CHCs), and urban-based district hospitals. Sub-centers are the most peripheral facilities providing communities with basic care. PHCs have slightly more capacity than sub-centers and provide curative and preventive care while acting as referal units for sub-centers. CHCs are small hospitals staffed with various medical doctors and equipped with surgical, labor, and x-ray facilities. Medical staff at district hospitals oversee activities at sub-centers, PHCs, and CHCs.

What is more likely is the third proposed reason, where JSY became operational but program funds were not distributed to households to the extent that they should have been. Many studies have documented low payment rates to eligible mothers. A March 2008 report by the Comptroller and Auditor General cites that during the fiscal years 2006-07 and 2007-08 only 57.5 and 82.0 percent, respectively, of women conducting institutional births received JSY funds. The United Nation Population Fund finds that only 64.8 percent of eligible mothers received the JSY transfer in 2008. There is plausibly variation in these percentages even within states. Therefore the lack of a significant structural break in the percent of women receiving benefits may be due to the receipt percentage being suppressed by program mismanagement and budgetary bottlenecks in certain districts. Based on this evidence, we use the estimated district-level program start dates from the mean shift model regardless of whether or not the estimated break date is significantly different from all other dates.

8.5 Description of Potential Factors Affecting Program Start Dates

Here we further motivate the inclusion of the seven categories of factors we identify as plausibly correlated with both JSY program adoption and mothers' use of medical facilities. First, the NRHM intends to focus on regions most in need of development. We therefore may expect districts which had very low institutional delivery rates before the program to be the first to implement. Socio-economic characteristics also could have influenced the timing; rural and poorer districts may have been targeted first, but they also may have taken longer to receive the program if the necessary infrastructure is less developed in these areas.

Third, the availability of medical facilities may have influenced program adoption. Districts with high patient capacity at public facilities likely were better equipped to begin a program that would increase demand for such facilities. Alternatively, high capacity at private hospitals could indicate people's preference for private medical care, dissuading local officials from rushing to implement JSY. Along similar lines, a fourth category of factors is people's preferences for health investments. Sorting yields higher variance of preferences across districts than within districts, and a population that values health relatively little may take longer to make the cash transfer available (Tiebout (1956); Epple and Sieg (1999)). We use three measures of a district's relative preference for heath investments: the percent of households that regularly treat their drinking water; the percent of villages that have formed a Village Health & Sanitation Committee (VHSC); and the percent of villages that discussed health related issues at *Gram Sabha* meetings in the prior year.[25]

[25] In an effort to address local needs of communities the NRHM ordered the formation of VHSCs in each village under the *Panchayat Raj* Institution. The *Panchayat Raj* is a system of local governance in which leaders are democratically elected. VHSCs have the role of developing a Village Health Plan, maintaining registers on health initiatives, providing feedback to relevant officials regarding health related issues in the

A fifth hypothesis is that the decision to adopt the program was affected by the extent of district-level ethnic fractionalization. A large literature exists on the inverse relationship between ethnic fragmentation and the quantity of public goods provided by local governments (see, *e.g.*, Alesina *et. al.* (1999); Miguel and Gugerty (2005); and Banerjee *et. al.* (2005)). While all districts were mandated to offer JSY benefits to eligible mothers, the decentralized nature of the program gave local authorities freedom over its implementation. Therefore, district-level ethnic diversity coupled with this freedom could be related to local leaders' willingness to offer the program as soon as possible. Since caste-affiliations play a strong role in local politics and program benefits were directed towards low-caste women, higher ethnic diversity could result in districts taking longer to coordinate the organization of District Health Societies, and therefore implement JSY.

A sixth category relates to the role of gender in affecting public good distribution and the actions of local governments. Chattopadhyay and Duflo (2004) show that the mix of public goods conforms more closely to the preferences of women when women are *Panchayat* heads. Clots-Figueras (2011) finds that female politicians in seats reserved for scheduled castes and tribes invest more in health and early education while favoring women-friendly laws. Since JSY is a program targeted to women it is plausible that districts with more female politicians were faster at its implementation. We test this using data on the gender composition of MLAs at the time each state approved the NRHM's Bylaws and ordered the formation of State and District Health Societies.

Finally, we consider political party affiliation among MLAs. The NRHM is one of the Central government's flagship development programs over the last decade, and since 2004 the Center has been controlled by the Indian National Congress (INC).[26] It is plausible that districts which are also dominated by the INC were faster at implementing its own party's program. For example, Ansolabehere and Snyder (2006) find that governing parties of US states skew the distribution of funds in favor of counties that provide them with the strongest electoral support (see, also, Shleifer and Vishny (1994)). Alternatively, non-INC politicians in districts with a strong opposition presence may purposefully have obstructed the implementation of INC legislation in order to undermine their opponent. Either story would indicate a higher proportion of INC MLAs should result in faster program adoption.

village, and creating awareness about health services and entitlements. The *Gram Sabha* is a constitutional body consisting of all persons registered in the electoral rolls of a village *Panchayat* with the responsibility of holding (at least) semiannual meetings for people in the village to discuss common issues.

[26]The INC lists the NRHM as one of its major accomplishments in a manifesto to voters during the 2009 parliamentary elections (INC (2009)). We recognize that Indian politics is comprised of coalitions of parties as opposed single party control. The makeup of these coalitions varies across both regions and time. For simplicity we limit our focus to analyzing whether or not a MLA is a member of the INC or the same party as his/her state's Chief Minister and do not consider possible coalitions of parties.

8.6 Description of Discrete-Time Hazard Model with Non-Linear Spline

To assess which of the factors presented in section 8.5 are correlated with JSY implementation dates we estimate a discrete-time hazard model of the probability of program adoption that allows for duration dependence. Consider the hazard rate (probability of implementing JSY), $Pr(t, X_d)$, as the likelihood that a district adopts JSY in the t-th month after already having gone $t-1$ months without implementation. Covariates X_d summarize the demographic, infrastructural, and political factors mentioned above of district d at $t = 0$. We specify the following logistic probability model:

$$Pr(t, X_d) = \frac{e^{[X_d\beta + f(t,\alpha)]}}{1 + e^{[X_d\beta + f(t,\alpha)]}}, \tag{8.2}$$

where β is a parameter vector and $f(t, \alpha)$ is a spline function determining properties of duration dependence. Traditional non-linear probability models assume duration independence. However, this assumption is violated if a district's action in one month is dependent upon its previous actions. Splines allow for a smoothed baseline hazard probability over predetermined intervals, and estimated coefficients on the spine intervals help trace out the path of duration dependence. Implicit in conventional spline models is a tradeoff between smoothness and goodness-of-fit. Increasing the number of polynomial functions improves the goodness-of-fit, but non-differentiability at the boundaries requires sacrificing smoothness. Further, limiting the number of intervals or the order of the polynomial functions yields a smoother curve but diminishes the capabilities of detecting complicated forms of duration dependence.

Following MaCurdy *et al.* (2014), we specify $f(t, \alpha)$ as:

$$f(t, \alpha) = \sum_{j=1}^{J} \left[\Phi_{j-1}(t) - \Phi_j(t)\right] \cdot \alpha_j, \tag{8.3}$$

where $\Phi_j(t)$ represents the CDF of a normal random variable with mean μ_j and variance σ_j^2, and α_j denotes a parameter vector. The functional form of the splines in equation (8.3) allows for α_j to represent $f(t, \alpha)$ over only a specified range of t. We set $J = 4$ (four intervals), and select values for μ_j and σ_j such that $\Phi_0(t) = 1$ and $\Phi_4(t) = 0$. In order to have a good fit, we set μ_1=10 months, μ_2=18 months, and μ_3=26 months, with the corresponding standard deviations equal to 3, 2, and 2, respectively. These values for μ imply that the intervals are [0,10], [10,18], [18,26], and [26,39], where 39 months is the longest time any district takes to adopt JSY. Results are fully robust to estimating the logit model with different spline values for μ and σ. Appendix Figures A5 and A6 show that the logit specification with splines fits the raw data well, but the model without splines over- and under-predicts the adoption probability over various time intervals. The non-monotonicity of duration dependence is evident in both figures; while the model without the spline function predicts a globally decreasing probability of adoption, the model with the spline allows for both increasing and decreasing probabilities over different time intervals.

8.7 Alternative Explanations for Changes in Institutional Delivery Rates

We explore two alternative explanations for changes in institutional delivery rates that are unrelated to JSY cash incentives. We show that compositional changes in the attributes of mothers, as well as district-level characteristics, are uncorrelated with the timing of JSY implementation. Regression results shown in Tables 4-6 include state and month fixed effects which help limit omitted variable bias from unobserved factors which vary across regions and time. These facts make it unlikely that some factor other than JSY is driving the results in section 6.1. Nevertheless, we consider here two alternative explanations.

8.7.1 Changes in Quality of Home Delivery

One possibility is that poor quality of care by mid-wives and traditional home-birth attendants caused women to opt for institutional delivery. For this story to be consistent with the aforementioned results, quality would have to have fallen in low performing states with little to no change in high performing states, and done so at the same time as increases in usage of public facilities. Figure A7 depicts changes in the quality of care for assisted home deliveries. Three measure of quality are shown: the percent of newborns that are immediately wiped dry and wrapped; the percentage of birth assistants that use a new or sterilized blade to cut the umbilical cord; and the percentage of birth assistants that use a disposable delivery kit.[27] Overall, these procedures/instruments were are utilized 58, 93, and 18 percent of the time, respectively. However, rates remain constant over the relevant period with no discontinuous changes. These quality measures change neither in high nor low performing states at the time of large increases in institutional deliveries. Furthermore, this hypothesis is unable to explain the small reduction in delivery rates at private medical facilities. We thus conclude that quality of care of home deliveries is not a viable explanation for our results.

8.7.2 Changes in Supply of Public Facilities

It is also reasonable to think that utilization of public medical facilities for child delivery increased due to increased capacity of these facilities. Although India's public health system

[27] Disposable delivery kits vary in contents but typically contain waterproof sheets, disposable gloves, soap, towels, a mucus extractor, condoms, oral contraceptive pills, and iron tablets.

is intended to provide access to rural communities throughout the country, many remotely located villages do not have access to public health care. In 2008 only 40.8 percent of villages sampled in the DLHS-III had a sub-center located within the village, and villages without them were on average 6 kilometers away from the nearest one. Part of the NRHM is aimed at addressing this lack of universal access by constructing new facilities in under-served areas, as well as focusing on upgrading poorly maintained facilities. With these efforts occurring around the same time as the introduction of JSY, it is possible that an increased supply of public facilities is leading to rising rates of institutional delivery.

We calculate the district-level number of PHCs, CHCs, and district hospitals per 1 million people from 2000 to 2008, as well as the number of labor beds per capita. These three facility types comprise 95.2 percent of all deliveries in public facilities. Figure A8 depicts the average across districts separately for high and low performing states. For this supply-driven hypothesis to hold, supply of public facilities would need to increase discontinuously at the same time that the rate of public deliveries rose in the end of 2006, and more so in low states than high states. The figure's top three panels show the number of facilities per capita. The number of PHCs and CHCs increases slightly each year over the sample period, but there are no noticeable discontinuities. Yearly increases occur from 2000 through 2005, yet as we have seen institutional delivery rates do not change over this period. District hospital availability remains fairly constant over the time period. The bottom three panels depict number of labor room beds per capita. There is a small increase in per capita PHC labor beds in low states in 2007 and 2008. However there is a similarly sized increase in per capita district hospital labor beds in high states in 2006 and 2007. If the uptick in PHC beds resulted in the large increases in public facility deliveries, we would also expect the uptick in district hospital beds to cause a rise in public deliveries. This,, however is not the case.

While we do not have intertemporal data on private facility capacity, the inclusion of month fixed effects in the earlier analysis helps control for aggregate changes in private capacity over time. Further, changes in private facility capacity are unlikely to induce women to switch from home births to delivery at public institutions.

Appendix Tables and Figures

Table A1:
Calculation of Priors and Signals of Facility Quality

Priors			Signals	
Question, Response	Measure 1	Measure 2		Measure
Why didn't you go to a facility for pre-natal care or delivery?			**Complications arising during delivery**	
Cost too much	0	0	Premature Labor	0
Too far/no transport/no time to go	0	0	Breech Presentation	0
Not Customary, Family didn't allow	0	0	Excessive bleeding	-1
Lack of knowledge	0	-1	Prolonged labor (12+ hours)	-1
Not necessary	-1	-2	Obstructed Labor w/o assisted delivery	-1
Poor quality service	-2	-3	Convulsions/eclampsia	-1
Was sufficient time given to you for your pre-natal care visit?			**Which services/advice were provided during your checkup within 48 hours of delivery?**	
Enough time	1	2	Abdomen examined	1
Somewhat enough time	0	0	Advice on breastfeeding	1
Not enough/Hurriedly	-1	-2	Advice on baby care	1
			Nutrition advice	1
Which services and information were provided at your pre-natal care visits?			Advice on family planning	1
Blood tested	1	1		
Sonogram/ultrasound done	1	1		
Delivery date told	1	1		
Nutrition advice	1	0		
Advice on need for cleanliness at delivery	1	0		
Need for institutional delivery	1	0		
Who motivated you to go to a facility for pre-natal care or delivery?				
Self or relatives	2	0		
Doctor, health worker	1	0		

Priors are measures of womens' beliefs over medical facility quality, relative to quality of care for home treatment, and are not facility-specific. Responses associated with relatively poor (high) facility quality receive negative (positive) point values, while those that do not speak directly to facility quality we treat as uninformative (zero value). Point values are aggregated across questions.

Table A2:
State-Wise Approval Dates of National Rural Health Mission By-Laws

State	State Type	Approval Date
Karnataka	High	May 2005
Haryana	High	July 2005
Tripura	High	July 2005
Uttarakhand	Low	July 2005
Madhya Pradesh	Low	August 2005
Uttar Pradesh	Low	August 2005
Chhattisgarh	Low	September 2005
Gujarat	High	September 2005
Rajasthan	Low	September 2005
Arunachal Pradesh	High	October 2005
Assam	Low	October 2005
Maharashtra	High	October 2005
West Bengal	High	October 2005
Meghalaya	High	November 2005
Mizoram	High	November 2005
Punjab	High	November 2005
Sikkim	High	November 2005
Andhra Pradesh	High	December 2005
Jammu Kashmir	Low	December 2005
Manipur	High	December 2005
Orissa	Low	December 2005
Bihar	Low	January 2006
Goa	High	February 2006
Jharkhand	Low	February 2006
Tamil Nadu	High	March 2006
Kerala	High	Unknown

Source: Ministry of Health and Family Welfare, Government of India, http://nrhm.gov.in.

Table A3:
Effect of JSY on Changes in Public Facility Quality

Covariates	(1)	(2)
No. of Months of JSY's Existence in the District	-0.001	-0.000
	(0.001)	(0.001)
Constant	-0.017	-0.029***
	(0.030)	(0.010)
Obs.	362	362
R-Squared	0.005	0.545
State Fixed Effects	No	Yes

Estimates by OLS. Dependent variable: difference between district-level public facility quality at SCs, PHCs, CHCs, and district hospitals from the DLHS-II (2003) and DLHS-III (2007-08). Quality is measured as an index of infrastructure, personnel, and supplies, including: presence of obstetricians, surgical and medical specialist, and pediatricians; regular water and electricity supply; biohazardous disposal methods; a pharmacy; cleanliness of wards, patient rooms, and the premises; and regular supply of medications including oral pills, tetanus vaccinations, iron and folic acid pills, and oral rehydration salts. Standard errors, which are clustered at the state level, are listed in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A4:
Tests of Correlation Between District-Level JSY Start Dates and District Characteristics

	Sample: All Districts						Sample: Significant (LRT) Districts					
	Bivariate Regressions				One Reg. w/ All Covars.		Bivariate Regressions				One Reg. w/ All Covars.	
	Coef./S.E. (1)	Constant	R^2	Obs.	Coef./S.E. (2)	Coef./S.E. (3)	Coef./S.E. (4)	Constant	R^2	Obs.	Coef./S.E. (5)	Coef./S.E. (6)
Pre-April 2005 Inst. Delivery Rate	-0.159	17.379***	0.188	581	-3.778	-10.009***	0.425	17.124***	0.276	384	-3.253	-12.754***
	(2.748)	(1.207)			(3.427)	(2.980)	(2.988)	(1.328)			(4.710)	(4.473)
% Rural HHs	-2.216	19.043***	0.189	581	1.778	-4.711	-2.129	18.965***	0.278	384	2.345	-5.824
	(2.442)	(1.910)			(6.544)	(3.381)	(3.075)	(2.387)			(6.546)	(3.732)
Ave. Wealth Index	1.152	17.313***	0.190	581	3.518	2.454	1.147	17.360***	0.278	384	3.637	2.999
	(1.280)	(0.003)			(3.693)	(1.772)	(1.387)	(0.057)			(4.038)	(1.934)
Public Hosp. Beds Per Capita	-0.006	17.487***	0.188	581	-0.005	0.007	-0.005	17.315***	0.276	384	0.001	0.004
	(0.014)	(0.395)			(0.017)	(0.019)	(0.017)	(0.472)			(0.020)	(0.022)
Ave. Distance to Private Hosp.	0.039	16.555***	0.187	569	0.036	0.019	0.013	17.134***	0.283	375	0.039	0.008
	(0.042)	(0.926)			(0.045)	(0.039)	(0.047)	(0.984)			(0.052)	(0.048)
% HHs Treating Water	-1.294	17.758***	0.188	581	-0.006	1.964	0.228	17.236***	0.276	384	-0.500	1.443
	(2.409)	(0.834)			(2.973)	(2.114)	(3.202)	(1.079)			(4.230)	(2.474)
% Villages with VHSCs	-2.437	18.084***	0.188	576	-2.620	0.196	0.356	17.228***	0.283	381	0.078	1.207
	(1.952)	(0.591)			(2.515)	(2.396)	(2.380)	(0.724)			(2.600)	(3.199)
% Villages Discussing Health at GS	-3.539	19.452***	0.189	572	-3.287	-2.546	-1.732	18.401***	0.286	379	-2.795	-1.766
	(2.641)	(1.553)			(2.856)	(2.236)	(3.913)	(2.289)			(3.661)	(2.906)
Ethnic Fractionalization Index	5.624	13.860***	0.192	581	2.947	3.316	6.116	13.443***	0.280	384	2.950	3.264
	(3.450)	(2.116)			(4.389)	(3.021)	(5.171)	(3.272)			(5.777)	(3.564)
% Female Politicians	-7.475**	17.788***	0.208	563	-7.616**	-7.770**	-10.250**	18.026***	0.300	378	-10.343**	-9.974**
	(3.446)	(0.219)			(3.644)	(3.549)	(3.695)	(0.260)			(4.049)	(4.061)
% Politicians from INC	1.310	16.936***	0.201	563	1.123	-0.375	2.834	16.536***	0.288	378	2.868	-0.177
	(2.169)	(0.623)			(1.996)	(2.093)	(2.659)	(0.721)			(2.385)	(2.462)
% Politicians Same Party as CM	-0.489	17.545***	0.200	563	-0.376	-0.946	-0.101	17.352***	0.282	378	-0.135	-0.461
	(1.589)	(0.755)			(1.670)	(1.477)	(2.004)	(0.962)			(2.311)	(1.772)
Constant					18.387***	24.666***					16.311*	26.509***
					(6.561)	(4.756)					(8.138)	(5.707)
Obs					548	548					368	368
R-Squared					0.219	0.082					0.323	0.122
F-Statistic					4.25***	4.31***					3.74***	4.68***
State FE	Yes				Yes	No	Yes				Yes	No

Estimates by OLS. The dependent variable is the number of months a district implemented JSY after its State began the NRHM. Standard errors are shown in parentheses and are clustered at the state level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Figure A1:
Map of Indian Districts: Delay in JSY Adoption After April 2005

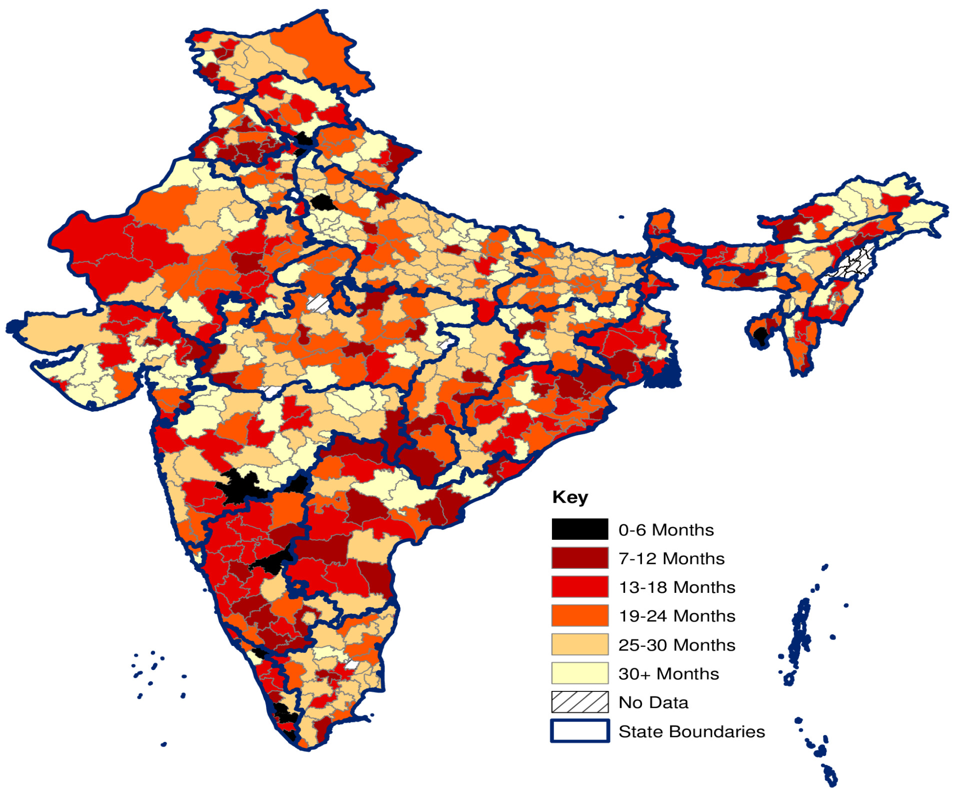


Figure A2:
Average Likelihood Ratio Statistic (Change in Receipt of Cash Transfer)

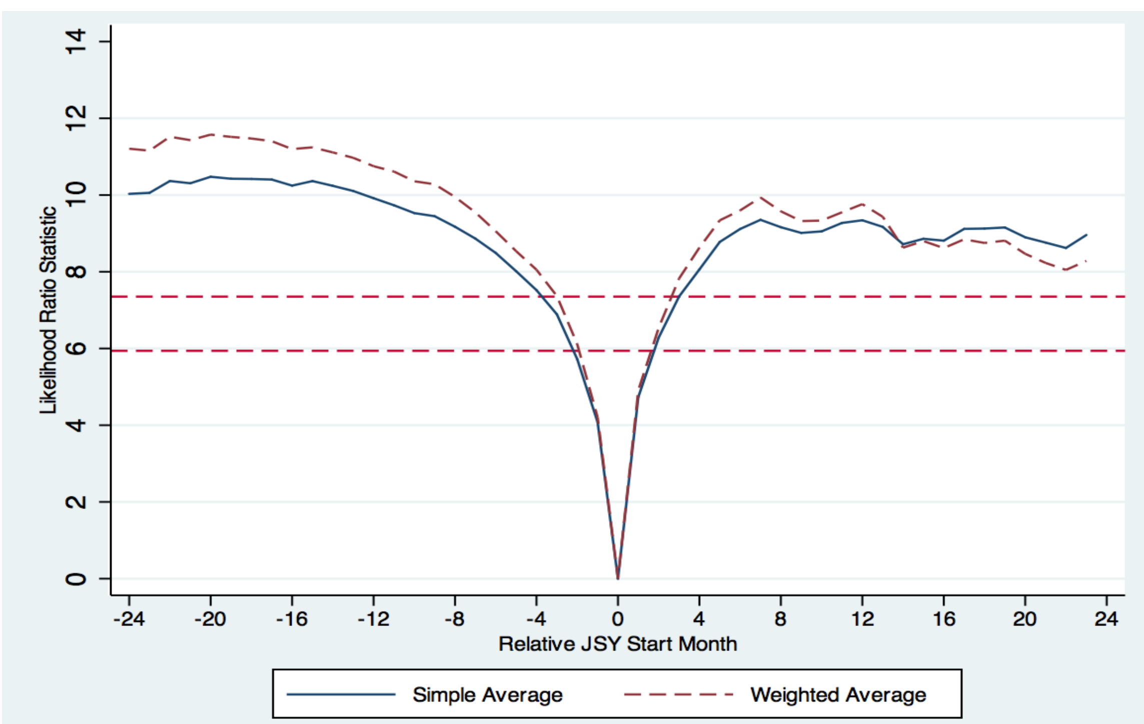


Figure A3:
Average Likelihood Ratio Statistic (Change in Rate of Institutional Delivery)

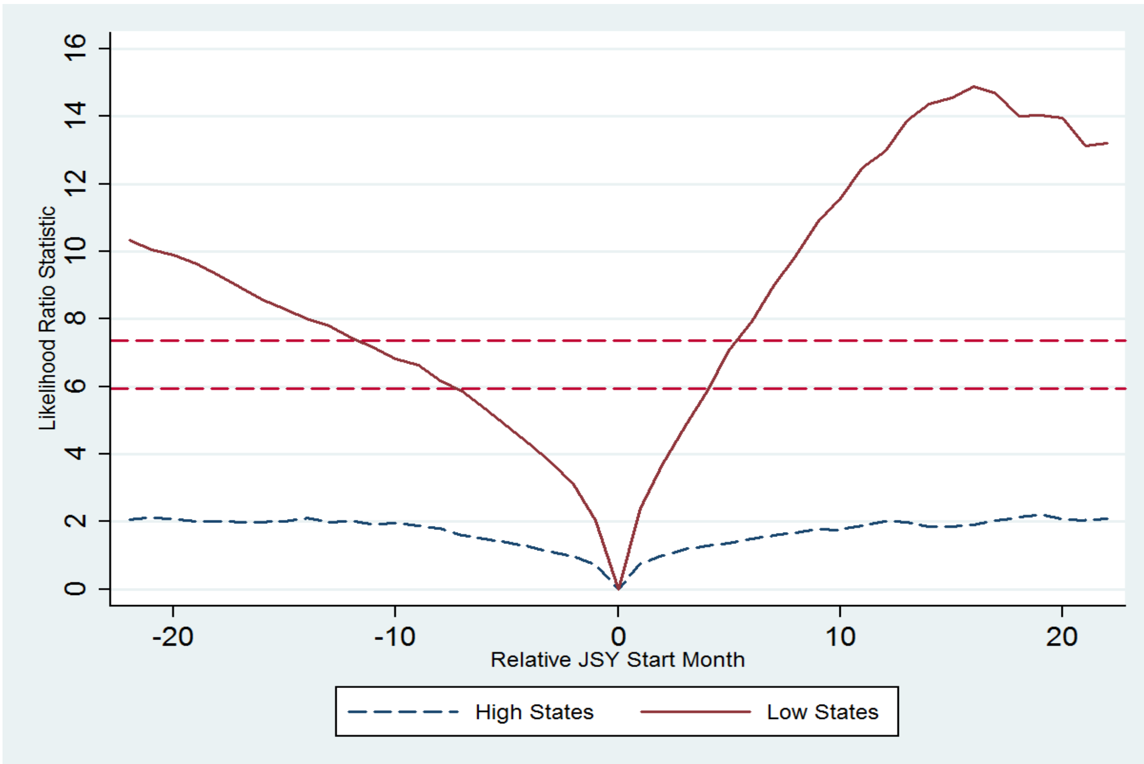


Figure A4:
Average Likelihood Ratio Statistic (Change in Mothers' Characteristics)

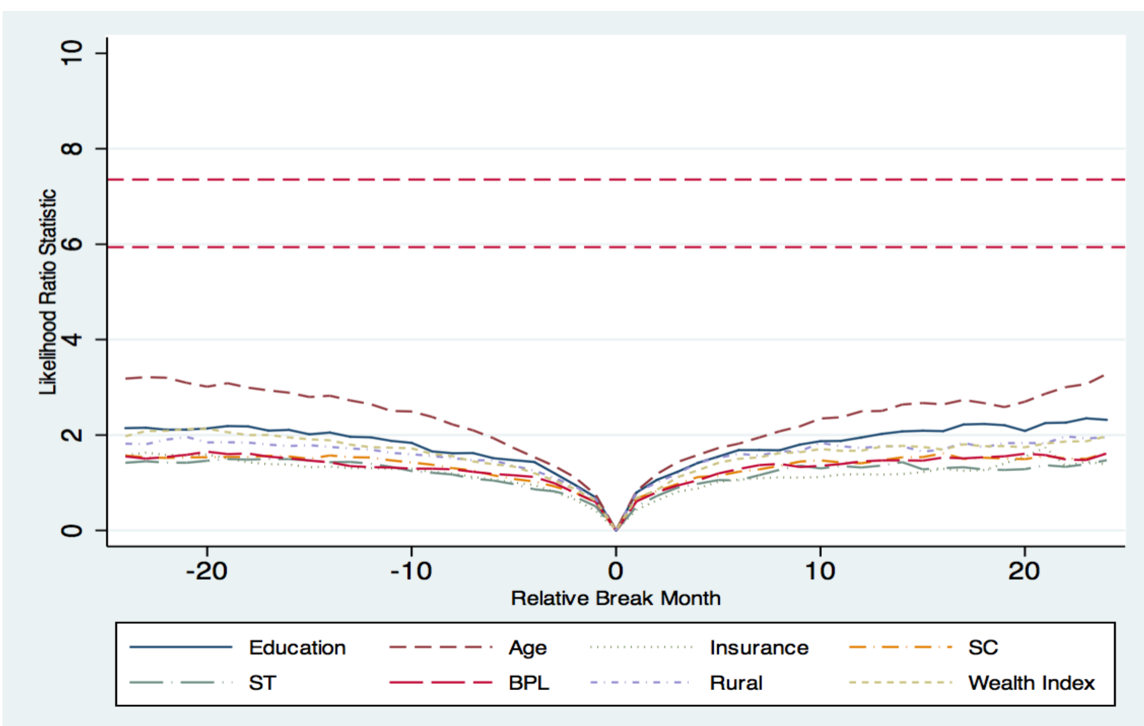


Figure A5:
JSY Adoption Probability by No. of Months After State's Adoption of NRHM

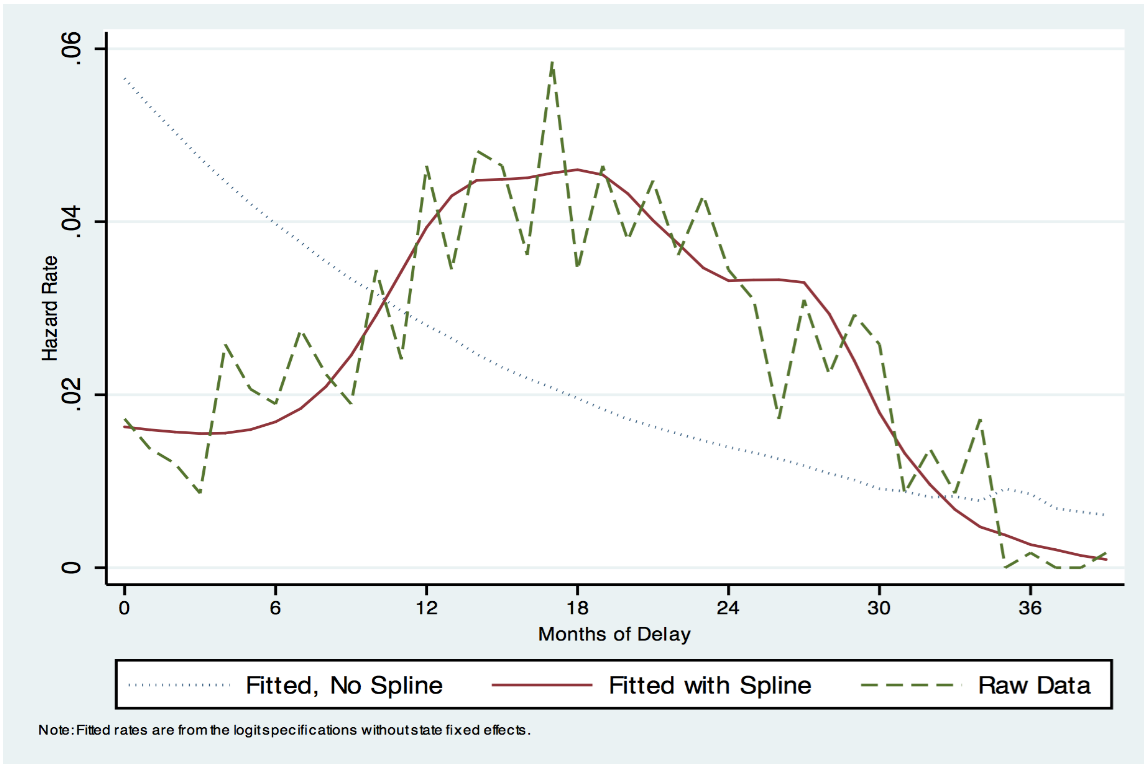


Figure A6:
Cumulative Probability of Adopting JSY by No. of Months After State's NRHM Adoption

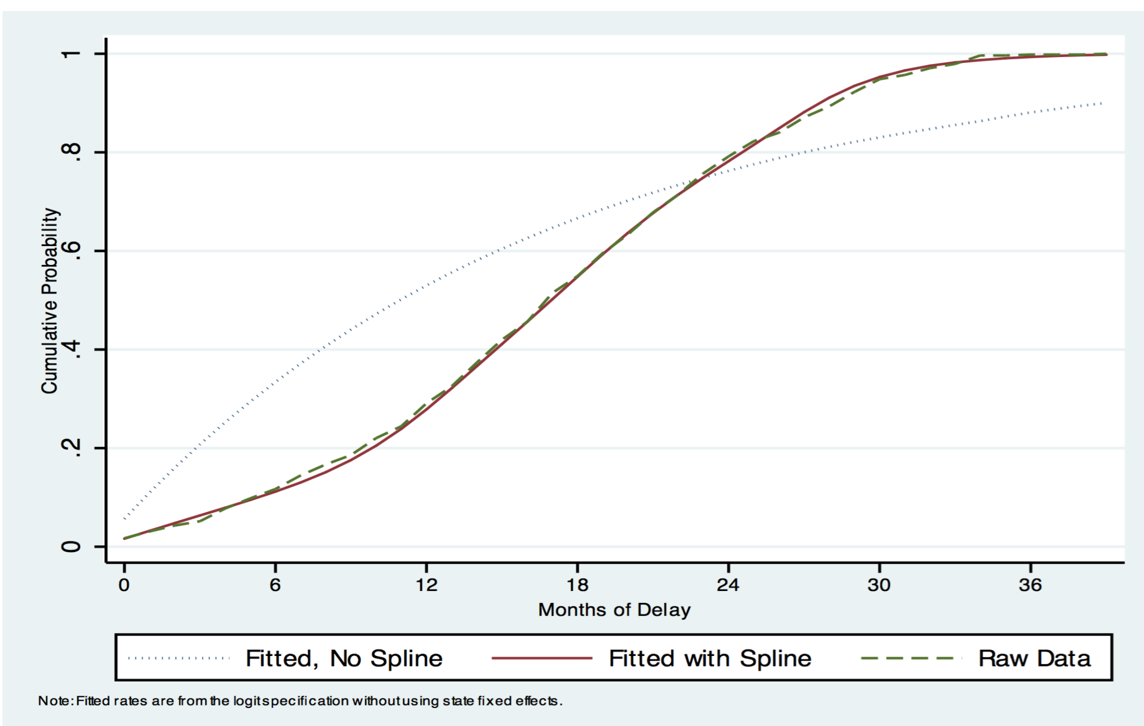


Figure A7:
Quality of Care for Home Deliveries

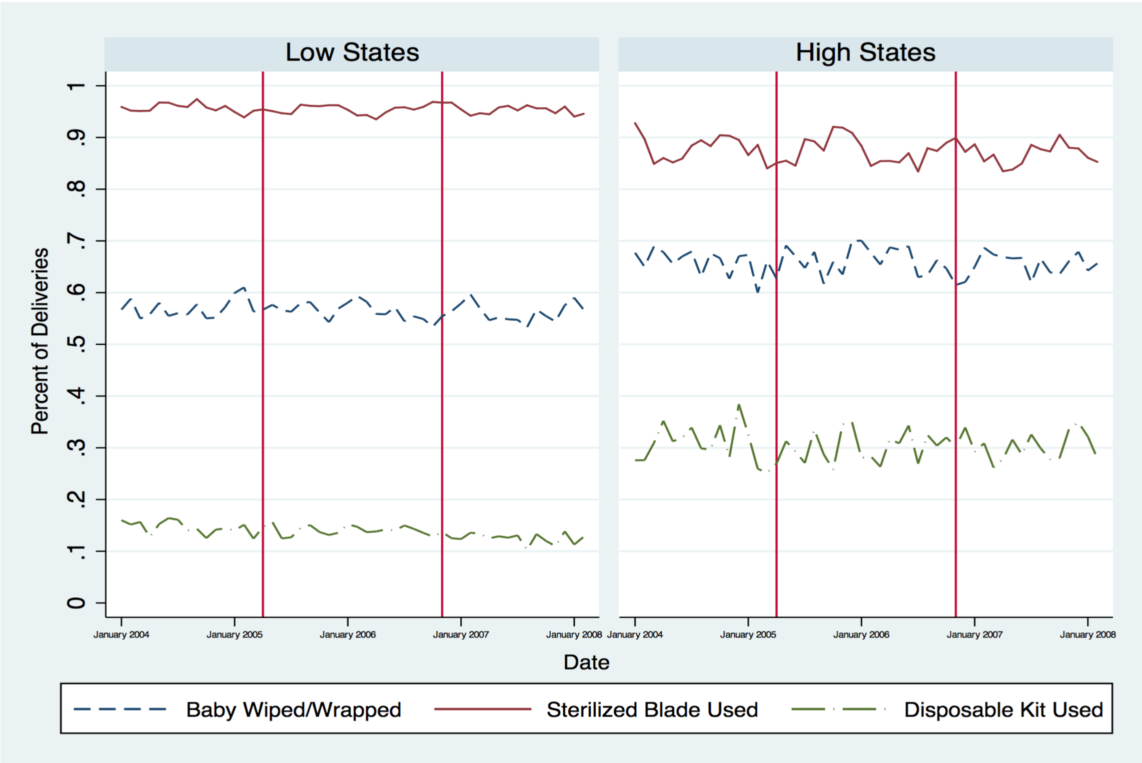


Figure A8:
Supply of Public Medical Facilities (District Average)