

Reassessment of the impact of India's Janani Suraksha Yojana conditional cash transfer program: A Replication Plan for Lim et al. (2010)

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Conditional cash transfer programs are becoming increasingly popular in low- and middle-income countries, with a goal of improving access to health and social services and reducing inequities in access and outcomes for the poor and marginalized. Policy makers need to better understand whether these programs are effective through rigorous evaluation of existing programs. India's conditional cash transfer program, *Janani Suraksha Yojana* (JSY), is one of the largest programs of its kind in the world. JSY provides financial incentives to pregnant women to encourage them to deliver in health facilities. This replication study, through robustness checks and additional model specifications, reexamines recent work on the effectiveness of JSY on maternal, perinatal, and neonatal health service utilization and outcomes. The research will specifically evaluate the original article's findings that JSY was associated with a reduction in perinatal and neonatal deaths.

Keywords: replication, conditional cash transfers, maternal health

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1. Introduction

India's conditional cash transfer program, *Janani Suraksha Yojana (JSY)*, is one of the largest programs of its kind in the world (Lim et al., 2010). Launched under the National Rural Health Mission (NHRM), JSY provides financial incentives to pregnant women to encourage them to deliver in health facilities. Cash payments are also offered to community health workers, called accredited social health activists (ASHAs), to facilitate institutional deliveries and promote other healthy reproductive and child health behaviors. Eligibility and financial incentives vary across states, with priority given to women in ten high-focus states. The program aims to increase access to safe pregnancy and delivery services, with the overall goal of reducing maternal and neonatal mortality and morbidity.

The annual number of beneficiaries of JSY grew from 734,000 in 2005-06 to over 10 million each year from 2009 onwards (MHFW 2013). The program reflects an important component of the Indian government's spending on health. With the launch of the NRHM, public spending on health increased by nearly 2.6 times between the 2004-05 and 2009-10 financial years (MHFW 2010), with a budget allocation for JSY estimated at \$342 million in the 2009-10 financial year (Lim et al., 2010).

2. Preliminary Literature Review

2.1 Conditional cash transfer programs: Overview

Conditional cash transfer (CCT) programs are increasingly being introduced in low- and middle-income countries, with a goal of improving access to health and social services and related outcomes, and reducing inequities in access and outcomes for the

poor and marginalized. A Cochrane review found evidence that CCT programs had a positive impact on the use of health services and the uptake of preventive services by children and pregnant women (Lagarde et al. 2009). A recent policy paper from the Center for Global Development focused specifically on the effects of CCT programs on maternal and newborn health reported that CCTs have increased antenatal visits, skilled attendance at birth, and delivery at a health facility, and reduced the incidence of low birth weight babies (Glassman et al. 2013). While both of these reviews include evidence from some programs that have been evaluated using well-designed studies, more rigorous evaluation is needed to assess the impact of these programs on health and utilization outcomes in different settings (Lagarde et al., 2009; Glassman et al. 2013).

2.2 Assessments of India's JSY program and the Lim et al. evaluation

As one of the largest cash transfer programs in the world, there has been much attention paid to JSY since its rollout in 2005. Evaluating JSY is critical to understanding its effectiveness in improving maternal and neonatal health outcomes, and reducing existing inequities in access and outcomes. The effectiveness of JSY is not only of importance for policy-makers within India, but could provide lessons for other countries with low rates of institutional delivery and poor reproductive health outcomes.

Lim et al. (2010) conducted the first formal statistical impact evaluation of JSY across the whole of India. Prior assessments of JSY were more descriptive in nature (Devadasan 2008), geographically limited in focus (UNFPA 2009; Sharma 2009), or considered only very limited outcomes (Satapathy, 2009). The Lim et al. (2010) paper has been a very influential study, widely cited in the literature and discussed in

international health economics and maternal health conferences over the last few years. (World Bank 2012, USAID Health Systems 20/20)

Despite its influence, there have been criticisms expressed regarding the findings of Lim et al.'s evaluation. Recent research has cited problems with the JSY program including corruption, poor quality of care, and slow or uneven implementation, leading to claims that the program has not been as successful as the results seem to suggest (Sukla 2012; Das et al., 2011; Mazumdar et al., 2011). Das et al. (2011) have called for a further review of JSY. Mazumdar and colleagues (2011) conducted the second national formal statistical assessment of JSY using the same data as Lim et al. (2010) but taking on a different statistical approach. Compared with Lim et al.'s (2010) results, Mazumdar et al. (2011) found a significant but smaller impact of JSY on in-facility delivery, little to no impact on antenatal care, and a lack of effect on reducing neonatal or early neonatal mortality. These are key program outcomes that are critical to understanding the success or failure of the program. Replicating the results of the Lim et al. (2010) study in light of these outcomes is important to confirm the validity and robustness of the results, and potentially address some of the criticisms that have been noted.

2.3 Main replication questions

We propose to replicate three key sets of results from the Lim et al. (2010) study:

1. Participation: What are the characteristics of JSY beneficiaries? Is the program reaching the target population?
2. Impact on coverage: What are reasonable estimates of the impact of the program on the following reproductive health coverage indicators: antenatal care,

institutional delivery, and skilled birth attendance, nationally, separately for high-focus and non-high focus states, and across selected key states?

3. Impact on health: Finally, and perhaps most relevant for policy, what is the impact of JSY on health outcomes? While the Lim et al. (2010) found no impact on maternal mortality, their findings of small but significant reductions in neonatal and perinatal mortality across two of their three methodological approaches are important, have been more controversial, and would be most interesting in being replicated and validated.

Others (Mazumdar et al. 2011) have already investigated variants of the delivery location and skilled birth attendance outcomes, such as the type of facility chosen for delivery, the health provider in attendance, and type of procedure(s) performed. We will not repeat these analyses that have already been explored.

3. Proposed replication plan

3.1 Pure replication

The replication will begin by validating the original results of Lim et al. (2010). We will begin by replicating the summary statistics of JSY uptake and the logistic regression to assess the associations between maternal receipt of financial assistance from JSY and individual and household characteristics. The most controversial findings of Lim et al. (2010) were the effect sizes of the estimates on antenatal care, institutional delivery, and neonatal and perinatal health outcomes (Mazumdar 2011). Given the matching analysis resulted in the most conservative, yet statistically significant estimated treatment effect for these four outcomes, we will focus only on the exact matching analytical approach, and replicate the results for these findings. We will not replicate the two

additional analytic approaches that the authors employ (Lim 2010). This is because the estimated treatment effects from the with-versus-without analysis were not statistically different from the exact matching analysis, and, similarly to the findings by Mazumdar and colleagues (2011), the authors found no significant effect of JSY on perinatal and neonatal deaths in the district-level differences-in-differences analysis (Lim 2010). Although reducing maternal mortality was a primary aim of the program, Lim and colleagues (2010) were unable to detect a significant effect of JSY on maternal mortality through the differences-in-differences analysis. The confidence intervals around the estimated treatment effect were very wide, giving little meaning to the computed effect, and the authors speculate that the survey was unpowered to detect the effect of JSY on the number of maternal deaths (Lim 2010).

We will maintain all of the authors' original assumptions and methods for aggregating districts, estimating household wealth and characterizing categorical variables, and implement the same exact-matching analysis with logistic regression.

3.2 Measurement and Estimation Analysis (MEA)

3.2.1 MEA: Alternative Matching Estimates

We begin the measurement and estimation analysis portion of this replication by alternating the matching estimator. The authors employ coarsened exact matching to preprocess the data and make the treatment variable as independent of background characteristics as possible. First, we will implement propensity score matching, a more widely-used matching technique, to compare the balance and robustness of the results under this matching method (Rosenbaum and Rubin, 1983). We will use the same set of

covariates as the original paper to compare the results using propensity score matching as compared to coarsened exact matching. Next, we will take advantage of the propensity score matching algorithm to match on additional covariates, namely, the full set of covariates used in the logistic regression analyses. This is not possible to do in coarsened exact matching due to limitations in sample size of the matching bins. Thus in their analysis the authors only matched on a limited number of characteristics. Propensity score matching will allow us to use a wider set of covariates than coarsened exact matching, without losing observations due to empty bins. We will check the robustness of the matching method by including the full set of covariates used in the logistic analyses when implementing the propensity score matching method.

3.2.2 MEA: Additional robustness checks

We will conduct additional robustness checks of the pure replication. First, we will conduct robustness tests of the definitions of variables, sample of analysis and model specification. We will examine the decisions the authors made about the definitions of the variables that they used, especially in the constructed index of household wealth. We will test the sensitivity of the results to these variations. For example, we will test whether leaving out or including other regressors, including interaction effects, changes the results in a significant way.

3.2.3 MEA: State level heterogeneity

Implementation of the JSY program varied considerably across states. Variation in the program included differential eligibility guidelines, amounts disbursed to women,

and payment processes. Additionally, states varied in their implementation and promotion of the program, which may have led to disparities in the awareness of the existence of the program. Finally, physical and cultural barriers in remote areas may have contributed to differential uptake of the program. The issues of differential eligibility, implementation, and uptake of the JSY program across states were documented by Lim et al. The authors conducted state-specific regressions for states with sufficient sample size, and found that the effect of JSY on in-facility delivery and skilled-birth attendance varied greatly by state. However, they did not show these data and presented only national-level treatment effects and treatment effects by type of state (high-focus, northeast, non high-focus) in their final analysis. Given the size and heterogeneity of many Indian states, these results can be quite important. We will provide results for the state-specific effects of financial assistance from JSY on health outcomes for states with adequate sample size.

We propose further investigating the state-specific effects to better illustrate the substantial variation among states as well as to identify the characteristics of states that had positive treatment effects compared to those with null or negative treatment effects. First, we propose a completely unpooled analysis. We will show the state-specific regressions for all outcomes and check the model fit of these regressions compared to the authors' pooled analysis. We anticipate that these unpooled analyses will not be precisely estimated due to small sample sizes.

Next, we will estimate a random effects model using Bayesian hierarchical methods. The random effects model is effectively a compromise between the completely unpooled and the fully pooled models. Formally, a model with random effects estimates

the unit-specific mean as a weighted average of the pooled estimate and the unit-specific estimate of the mean. Our units are the Indian states, where we believe exists important heterogeneity. The weights that contribute to the weighted average are the precisions of the pooled estimate and the state-specific estimate. Because some of the states have small sample sizes, a completely unpooled fixed effects analysis will yield highly variable estimates for those states. With the random effects model, we borrow strength across states to improve individual state estimates. For larger states, we have good estimates, while for smaller states, we borrow information from other states to obtain more accurate estimates. The states with small sample sizes are “shrunk” towards the overall pooled mean. This framework allows us to deal with the cross-state heterogeneity (Gelman et al. 2004).

To describe the Bayesian model further, the state means are drawn from a distribution, i.e. $\mu_j \sim N(\mu, \tau^2)$ where μ_j is the state specific mean for state j , μ is the overall pooled mean, and τ^2 is the between-state variance. This is our prior distribution for μ_j . The data y_{ij} are drawn from a normal distribution with mean μ_j and variance σ^2 . This results in a shrinkage factor of $B_j = \sigma^2 / (\sigma^2 + \tau^2)$, which is the ratio of the within-state variation to the total variation. This estimation method results in a smaller mean squared error for better overall estimation of the state specific effects of JSY (Goldstein 1995).

There may be limitations in our planned heterogeneous impact analysis in that sample sizes of some states are small. JSY was also not implemented across all of India over the time period for which we have data (Mazumdar et al. 2011). We hope to address some of these limitations with the use of our Bayesian hierarchical model, which uses the national mean as a prior on each state level coefficient. Thus, for states with very little

data, the state level mean will be shrunk to the national mean. When we conduct the completely unpooled analysis, we will focus on the states that do have enough sample size and hope to show that even among those states, there is a great deal of heterogeneity in impact size. Finally, using propensity scores to match instead of coarsened exact matching will greatly reduce “the curse of dimensionality” problem, that is, that individuals differ a great deal in many characteristics and it is difficult to match on all dimensions. Propensity score matching reduces all characteristics into one propensity score that is included in the regression equation, which we hope will improve our estimates for the heterogeneous impact analysis.

3.2.4 MEA: District level heterogeneity

Uneven implementation of the JSY program across districts can lead to a problem of endogeneity in the treatment variable (Mazumdar 2011). For example, it is possible that districts with greater JSY coverage were also more likely to be effective in other ways that affect health outcomes. There may be omitted variable bias in that even after matching for observable characteristics as Lim et al. (2010) did, there remain significant unobservable district-level characteristics, such as management ability and capacity of district health authorities.

The analysis by Mazumdar et al. (2011) employs a differences-in-differences estimation that exploits the heterogeneity in the timing of the introduction of the JSY programme across districts. The authors identify the year in which JSY was first introduced in a given district, and use this as an indicator to instrument for coverage of JSY. Interactions between year of birth and district-level characteristics (e.g., share of the

population below the poverty line, tribal population share), were included to control for potential sources of endogeneity in the timing of JSY introduction. The authors' IV strategy leads to an impact parameter that can be interpreted as the effect of JSY at full coverage. The strength of their approach is that it controls for time invariant unobservables at the district level that may influence study outcomes and be correlated with the introduction of JSY. Unlike the Lim et al. (2010) district-level differences-in-differences approach, Mazumdar's approach uses individual-level data, which allows for sufficient power to estimate the effect size for the health outcomes (excluding maternal mortality).

We will not repeat what Mazumdar and colleagues have already done, and instead propose to address the differential implementation of JSY across districts through several different approaches. First, we propose including district as a matching covariate within the propensity score matching analysis and re-estimating results. Although this would not have been possible in the exact matching approach due to limitations in bin sizes, this can help to control for time invariant unobservable differences across districts that could be related to the scale-up of JSY. Next, relying on methods by Mazumdar et al. (2011) that explore the heterogeneity in the timing of the introduction of JSY across districts using facility-level data, we will re-estimate the results restricted to districts that had clearly implemented JSY during the study period. This will reduce biases related to unobservables that may influence study outcomes and be correlated with the introduction of JSY during the study period. We will also explore the effect of restricting the sample to births in the last 12 months prior to the survey, in relation to this issue of differential implementation of JSY across districts. We will demonstrate what happens to the

estimates under the new model specifications. If the bias is not strong, then the estimates should not change very much compared to the original analysis.

3.3 Limitations

One of the potential limitations of any analysis seeking to evaluate the impact of JSY on institutional delivery is the issue of reverse causality: women receive the cash incentive upon delivering in a health facility (Mazumdar 2011). While we are unable to address the issue of reverse causality in this replication exercise, we suggest further qualitative analyses on the role of ASHAs in facilitating or motivating women to seek antenatal care and deliver in a health facility. Two survey questions in particular, “Who facilitated or motivated you to avail of antenatal care?” and “Who facilitated or motivated you to go to a health facility for delivery?” could be used for this analysis. Both of these questions were asked prior to the question about whether women had received financial assistance from JSY for their most recent delivery. We propose to explore whether women who received financial assistance from JSY were more likely to report receiving assistance or motivation from an ASHA in response to these questions.

4. Conclusion

This replication aims to validate the original findings from Lim et al. by replicating the key coverage and health outcome results using the same assumptions and empirical models that the authors employ. We will begin with alternate specifications of the matching model and examine the robustness of the results under the more commonly used propensity score matching algorithm. Following this, the replication will examine

alternative methods for accounting for the heterogeneity of state and district effects including state-specific unpooled analyses, a Bayesian hierarchical model, and analyses that explicitly take into account the implementation of JSY across districts. Finally, we will investigate in a qualitative way one of the possible pathways through which the JSY program may be operating, by exploring the role of ASHAs in motivating women to seek antenatal care and to deliver in a facility.

Ultimately, the replication is intended to verify and examine the robustness of the findings from Lim et al. (2010). Conditional cash transfers are poised to make significant contributions to the health of people in developing countries. However, it is critical to understand under what conditions these transfers are successful. The JSY program was one of the one of the largest cash incentive programs for health in the world. Evaluating this program has important implications for future health interventions and policies to improve health in developing countries. Therefore, ensuring the robustness of the results found by Lim et al. (2010) is a meaningful exercise for the future of development policy.

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