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Incentivizing Demand for Supply-Constrained Care: Institutional Birth in India*

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Abstract

We examine how the effects of incentivizing individuals to use healthcare depend on the capacity of the health system. We study a conditional cash transfer program (JSY) in India that paid women to give birth in medical facilities. We find that JSY doubled the number of deliveries for which the average facility was responsible. In areas with below-median capacity, JSY increased perinatal mortality. Adverse effects spilled over onto rates of childhood vaccinations suggesting a diversion of resources from routine services. Our results indicate that health-system capacity is of first-order importance in determining whether demand-side policies are beneficial or harmful.

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1 Introduction

It is increasingly common for governments to incentivize individuals to use healthcare.[1] The rationale is clear; barriers, such as a lack of information or a lack of resources, might prevent individuals from seeking out beneficial care. However, health systems in many low- and middle-income countries (LMICs) that use demand-side incentives are often poorly resourced and provide poor quality care.[2] Given this, incentivizing demand could backfire. When healthcare quality is poor, the marginal group who take up care due to the incentive may not benefit from the care, and the care may even be harmful for them. Moreover, if the additional demand causes fixed resources to be spread more thinly, then the quality of care may fall. Finally, to manage an increase in demand for the incentivized area of healthcare, providers may substitute effort and resources away from other areas of care, which could risk a wider deterioration in quality.

In this paper, we examine these issues in the context of the world's largest conditional cash transfer program: India's Janani Suraksha Yojana (JSY). Introduced in 2005, JSY pays substantial cash incentives – around 28 times the average rural daily wage for casual labor – to women who give birth in a health facility.[3] The scheme does not provide increased funds to facilities to cover the cost of additional deliveries. JSY is widely credited with causing a rapid decline in home births, which fell from 80% in 2005 to 40% in 2011 in the states where the program focused.[4] Yet rigorous research has found that it had no overall impact on birth outcomes (Powell-Jackson, Mazumdar, and Mills 2015). This is puzzling since a set of simple medical procedures can mitigate the vast majority of mortality risks associated with childbirth for both mother and infant (Lawn et al. 2005). The pervasive

[1]Conditional cash transfers, for example, operate in 64 countries and many condition payments on the take up of healthcare (World Bank 2015).

[2]See, for example, Das et al. (2016), Das et al. (2008), Mohanan et al. (2015), Das et al. (2015), Daniels et al. (2017), Das et al. (2012) and Sylvia et al. (2015).

[3]JSY payment is Rs. 1400 in the states we focus on (see Section 2). Average daily wage rates for casual labor (across rural areas of all states) in 2004/5 was Rs. 48.89. By contrast average daily wages for regular employment were Rs. 133.81. Figures taken from 61st round of the NSS.

[4]Authors' calculations using DLHS-III and NFHS-IV.

poor quality and low capacity of India's government health system provides a potential explanation for why bringing births into medical facilities had no overall effect on health. Relative to national income India's public spending on health is a third of other major emerging economies and the system has a huge shortage of qualified health professionals (Rao et al. 2011) compounded by high rates of absenteeism (Banerjee et al. 2004; Chaudhury and Hammer 2004; Chaudhury et al. 2006).[5] Two years before the launch of JSY, in the areas where the program focused, the proportion of districts that met government standards for having sufficient beds in secondary health facilities was 36.5%. The proportion with sufficient doctors was 41.2%, and with sufficient nurses and midwives, 16.5% (Figure 1).[6]

In this study, we explore the effects of incentivizing the demand for healthcare in this highly supply-constrained system. First, we use geographic disparities in the pre-existing capacity of district health systems – disparities caused by central governments' allocation of funds and variation in states' political priorities (Kumar et al. 2011) – to assess how the effects of stimulating demand depend on supply constraints. Specifically, exploiting exogenous variation in JSY's rollout, we examine whether the pre-existing numbers of doctors, nurses, and beds (relative to the size of the population served) in both primary and secondary health facilities affected its effects. Second, we consider whether the increased demand for services related to childbirth had spillover effects on the quality of other services provided by health facilities. In particular, we assess the impact of JSY on rates of childhood vaccinations.

We find that JSY led to a large average increase, of 7.86 percentage points, in the probability that births were delivered in health facilities. In aggregate, this doubled the number of institutional deliveries per day for which each secondary care facility was responsible. The increase in deliveries per facility was particularly stark in districts with below-median capacity in the secondary care system (in terms of numbers of beds, doctors, and nurses

[5]India's public spending on health accounts for 0.9% of GDP while Brazil spends 3.9% of GDP, Russia spends 3.0%, China spends 2.9%, and South Africa spends 4.4%. Figures taken from 2016 Domestic General Government Health Expenditure from Global Health Expenditure Database: http://apps.who.int/nha/database. Corresponding figures for 2005: 0.8% for India, 3.3% for Brazil, 3.1% for Russia, 1.4% for China, and 2.8% for South Africa.

[6]As elaborated in section 3, these figures understate the lack of resources.

relative to the population). Here caseload increased by a factor of 2.5, from 1.92 deliveries per facility per day to 4.80.

We show that in these districts with below-median capacity in the secondary healthcare system, the average risk of perinatal mortality *increased* as a result of JSY by 0.90 percentage points, or by 24.3% relative to the rate prior to JSY. While JSY caused the same increase in the rate of institutional delivery in areas with above-median pre-existing capacity, it had no overall impact on perinatal mortality in these areas. Still, in these areas JSY did not succeed in decreasing mortality. The effect of JSY on perinatal mortality is the weighted average of two channels: the effect of institutional delivery on the mortality risk for marginal (or complier) births induced into facilities by JSY, and the effect of the program on the mortality risk associated with institutional delivery (for marginal and inframarginal births). Both channels suggest that supply-side factors prevented an increase in demand for institutional delivery being translated into improved birth outcomes. We use a bounding argument to suggest that the magnitude of the effects makes it likely that at least some portion of the mortality effect arose from an increase in the risk associated with institutional delivery for inframarginal births.

We also find that stimulating demand for institutional delivery had adverse spillover effects on another service that health systems provide: it came at the expense of childhood vaccinations. The proportion of children who were up to date with all vaccinations fell by 2.05 percentage points.

Our findings have clear implications for policy. They show that the capacity of a health system to deliver a rapidly increasing amount of the incentivized care, at sufficient quality and without reducing the quality of services, should be a first-order consideration when deciding whether to adopt demand-side incentives. They demonstrate that stimulating demand without a high-quality and adaptable supply side may have perverse effects, both on the area of healthcare originally targeted and on other areas. These considerations are likely to be particularly crucial in decisions about whether to incentivize the take-up of invasive, time-consuming, and potentially risky procedures like institutional delivery.

Consequently, this paper contributes to several literatures. First, it contributes new evidence on demand-side incentives, which feature prominently in debates about improving health outcomes in LMICs (Dupas and Miguel 2017; Kremer and Glennerster 2011). Although such incentives are generally effective at increasing uptake of care (Giedion and Díaz 2010; Lagarde et al. 2009), there is substantial heterogeneity in their effects on health. For less invasive health interventions, such as the health check-ups, vaccinations, or nutrition advice that early conditional cash transfers in Latin America typically incentivized, health benefits have sometimes, but not always, been found (Lagarde et al. 2009; Attanasio et al. 2005; Gertler 2004; Maluccio and Flores 2005; Morris et al. 2004; Rivera et al. 2004; Behrman and Hoddinott 2005). However, when demand for more invasive procedures, which could plausibly increase risk if delivered poorly, has been targeted with no change to the supply side, studies have generally not found health benefits (Giedion and Díaz 2010; Powell-Jackson et al. 2015; Okeke and Chari 2015). Conversely, where the supply side has been improved simultaneously, health benefits have often followed (Gruber et al. 2014; Miller et al. 2013; Cesur et al. 2017). Our paper contributes by directly examining the role of supply in explaining heterogeneity in how demand-inducing policies affect health. We do so within a single health system and focus on invasive procedures whose riskiness depend directly on quality.[7]

Second, this paper adds to evidence on the importance of healthcare quality. Good quality care is crucial to ensure that efforts to universalize access to medical care actually translate into improved health (Kruk et al. 2018; Scott and Jha 2014). The quality of the healthcare that individuals receive will depend on the inputs that are used and the effectiveness with which the health system transforms these inputs into health outcomes for patients (Hanefeld et al. 2017). In many health systems in low- and middle-income countries, including in rural India, inputs such as trained health professionals and equipment are often not effectively

[7] Evans et al. (2017) find that, in Tanzania, cash transfers conditional on health clinic visits led to a greater reduction in the number of self-reported sick days in villages with more health workers.

translated into evidence-based care (Das et al. 2018). Nevertheless, we show that even if existing health professionals and equipment are not used as effectively as they might be, their availability can still be an important predictor of how an increased use of healthcare translates into health outcomes.[8] Interestingly, we find that capacity in secondary health facilities is a very important predictor of the impacts of increasing institutional deliveries on health. Delivery care is long and invasive, and the increase in the number of deliveries due to JSY was large; together, these factors suggest that supply-side constraints in the number of professionals and equipment may be particularly important in this context.

The third literature we contribute to considers on the spillover effects from policies that target one aspect of healthcare onto another, in line with Holmstrom and Milgrom (1991). Previous work has found that health providers increase their use of procedures that are incentivized in reimbursement contracts (Hennig-Schmidt et al. 2011), and this increase is often, but not always (Celhay et al. 2019), at the expense of non-incentivized tasks (Shearer et al. 2018; Dumont et al. 2008; Gruber et al. 2018). Our paper is the first to assess whether incentivizing the *demand* for certain procedures leads to a deterioration in the use or quality of others. We find that it does. Whether such reallocations are optimal depends on the relative productivity of different procedures. In this case, however, the reallocation of resources induced by JSY provided no aggregate health benefits but caused a reduction in childhood vaccinations.

Finally, this paper fits into a small literature on the effects of JSY. Previous work has demonstrated that the program had no effect on birth outcomes (Powell-Jackson et al. 2015; Das and Hammer 2014; Ng et al. 2014; Randive et al. 2013) and has commented that the pervasive poor quality of healthcare likely underlies this (Chaturvedi et al. 2014).[9] Similarly, programs in Malawi and Rwanda that also increased institutional delivery rates

[8] While it might be the case that the presence of health professionals and beds are correlated with other drivers of care quality, we consider it likely that these physical and human resources are causally important determinants of quality in our setting.

[9] Another program, Chiranjeevi Yojana, that covered the cost of deliveries at designated private health facilities for Below-Poverty-Line women in Gujarat improved neither institutional delivery rates nor health outcomes (Mohanan et al. 2014).

did not improve health (Godlonton and Okeke 2016; Okeke and Chari 2015). This is the first paper to assess heterogeneity of impacts by pre-existing health-system capacity. It is also the first to assess whether JSY had knock-on impacts on other services.

This paper proceeds as follows. Section 2 provides a basic overview of JSY while Section 3 discusses our data, choice of sample and construction of measures. Section 4 presents our methods and results for assessing the impact of JSY on institutional delivery and perinatal mortality, Section 5 does the same for vaccinations and Section 6 assesses the robustness of findings. Section 7 concludes.

2 JSY

JSY was launched in April 2005 and aimed to reduce maternal and infant mortality through increasing rates of institutional delivery (Ministry of Health Family Welfare Government of India 2005).

In this paper, we focus on JSY's effects on rural households living in states where the scheme focuses most of its attention. These are the states designated as "Low Performing States" based on their low prior rates of institutional delivery. For rural households in these states JSY is universal and cash incentives are more generous than in either "High Performing States" or in urban areas. Specifically, JSY provides financial incentives of Rs.1400, or USD 32, to all pregnant women who give birth in a government health facility.[10] It also provides incentives of Rs. 600, or USD 14, to community health workers for every pregnant woman they bring to a facility. By contrast, in High Performing States only pregnant women with a Below Poverty Line card are eligible and transfers are lower than in Low Performing States (Rs. 700 *vs.* Rs. 1400). Rural births receive higher transfers than urban births (Rs. 1400 *vs.* Rs. 1000).

JSY has subsequently transitioned to using digital payments, but during the period

[10] Exchange rate: 44 Rs./USD (April 2005).

we study cash was given to women delivering in health facilities. Cash should have been distributed within one week although reports of delays, and women only receiving partial payment, were common (Devadasan et al. 2008).

While policy documents mention, for example, "operationalisation of 24/7 delivery services at [primary health centres] level to provide basic obstetric care" and "operationalisation of First Referral Units (FRUs) to provide the emergency obstetric care", JSY did not provide any additional funding to help health facilities expand obstetric services (Ministry of Health Family Welfare Government of India 2005).

3 Data and Sample

We focus our analysis on the households JSY primarily targeted: rural households in the nine states JSY designated as "Low Performing States".[11] Together, the rural population of these states comprised 33.9% of India's population in the 2001 census and 48.7% of India's deaths of infants under seven days of age between 1990 and 2001.[12]

3.1 Perinatal Mortality, Place of Birth and Vaccinations

Data on perinatal mortality, defined as stillbirth after 22 weeks of pregnancy or death within seven days of birth, come from the 2007/8 DLHS-III pregnancy roster for ever-married women, which recorded all pregnancies since January 1, 2004. We focus on perinatal mortality given its particular sensitivity to the quality of care during the birth (World Health Organization 2006). We use all births – i.e. live births and stillbirths but excluding miscarriages and abortions – that occurred between January 1 2004 and December 31 2007 and within nine quarters of JSY's rollout in the district as our sample. We thus drop the 36

[11] Uttar Pradesh, Chhattisgarh, Bihar, Madhya Pradesh, Rajasthan, Assam, Orissa, Jharkhand and Uttarakhand. Jammu and Kashmir was also designated a "Low Performing State" however we estimate that JSY only began in a single district before 2008 and so we drop it from all analysis.

[12] Calculated from DLHS-II using sample weights.

districts where JSY was not rolled out until after quarter 4 of 2007 which leaves us 256 districts. Table 1 provides sample descriptives.

Place of birth (home, hospital etc.) is available for each respondent's most recent birth, and vaccination data are available for each respondents' two most recent surviving children. Given polio vaccinations are largely administered by a parallel system, the "Pulse Polio Initiative", we focus on the 6 non-polio childhood vaccinations that are delivered through the public health system: BCG (for tuberculosis, recommended at birth), 3 doses of Diptheria-Pertussis-Tetanus (DPT, 1.5, 2.5 and 3.5 months), Measles (9 months) and Vitamin A (9 months). Where possible, vaccination data was collected directly from children's vaccination cards. However, in 70.2% of cases the respondent did not have a vaccination card, or did not share it with the interviewer, and the data was collected by maternal report.

Since data on place of birth and vaccinations are only available for each mother's most recent birth(s), a sub-sample of disproportionately higher birth order, estimated effect sizes should be interpreted as averages for these sub-populations. Given that birth order affects both birth outcomes and parental health investments (Jayachandran and Kuziemko 2011; Jayachandran and Pande 2017) we control for birth-order fixed effects throughout.

3.2 Capacity

We construct measures of pre-existing capacity in each district using three inputs that are easy to measure and over which national guidelines exist: (i) beds, (ii) doctors/medical officers, and (iii) nurses/midwives. We distinguish between inputs in primary health centers (PHCs), the first point of contact for patients, and secondary or referral facilities, which have more specialized staff and equipment.[13]

We use the facility survey of the DLHS-II which, in 2003, surveyed government health facilities in 370 of India's 640 districts and for 182 of the 256 districts we focus on in this

[13] Secondary facilities comprise district hospitals, community health centers, rural hospitals, and first referral units.

Table 1: Sample Descriptives

	Mean	Standard Deviation	N
Birth Outcomes			
Perinatal Mortality	0.0398	0.195	104057
Stillbirth	0.0153	0.123	104057
Died within 7 days | Live birth	0.0248	0.156	102461
Place of Birth			
Home	0.723	0.447	81242
Government Hospital/CHC	0.124	0.330	81242
PHC	0.0598	0.237	81242
Private/NGO Hospital/Clinic	0.0926	0.290	81242
Vaccinations (Up to Date)			
BCG	0.800	0.400	96284
DPT-1	0.734	0.442	95886
DPT-2	0.639	0.480	95175
DPT-3	0.543	0.498	93894
Measles	0.659	0.474	79298
Vitamin A	0.582	0.493	79298
Mean	0.665	0.388	79298
Mother Characteristics			
Age	24.34	5.432	104057
Husband's age	30.53	11.20	104057
Age at marriage	16.32	3.413	104057
Years of education	7.184	2.057	104057
Household Characteristics			
Number of married women	1.851	1.042	104057
Number of married women	1.549	0.946	104057
Wealth index	0.180	0.130	104057
Scheduled caste	0.198	0.399	104057
Scheduled tribe	0.164	0.370	104057
Other backward class	0.446	0.497	104057
Below poverty line	0.333	0.471	104057
Hindu	0.860	0.347	104057
Muslim	0.122	0.327	104057

Notes: Table presents descriptive statistics of births in the sample. Place of birth is available for each respondent's most recent birth, and vaccination data are available for each respondents' two most recent surviving children. Vaccination variables only defined for children older than the recommended age of administration.

paper.[14] These data cover all secondary health facilities and a random sample of PHCs.[15] We estimate the number of beds, doctors and nurses/midwives per 10,000 of the rural population in each district's primary and secondary care facilities using population figures from the 2001 census. We scale the primary care ratios by the number of PHCs in the district in 2004 and trim all capacity measures at the 99th percentile.[16]

Figure 1 graphs the density of these capacity measures across districts, indicating the Indian Government's 'standards' and 'recommended' levels (Directorate General of Health Services and Ministry of Health Family Welfare 2006) which, as already discussed, the vast majority of districts fell far short of. These figures underestimate the proportion of districts falling short because our measures do not account for population increases between 2001 and 2004 and because the cut-offs for secondary care include only the standards for community health centers but not other secondary facilities.

We use exploratory factor analysis, adopting the principal-component method, to assess the dimensionality of these six measures, and to create summary indices. We first assess dimensionality by running a single factor analysis. We estimate and rotate two orthogonal factors with eigenvalues greater than one (the Kaiser criterion for retaining and rotating a factor (Kaiser 1960)) which implies that these six measures can be well summarized by two underlying factors: one primarily being informative for measures of secondary capacity and the other for measures of primary capacity (factor loadings shown in columns (1) and (2) of Table 2). We next run two separate factor analyses for the primary and secondary capacity measures to create summary indices for each without imposing orthogonality. These are the indices that we use in our analysis and columns (3) and (4) show the loadings.

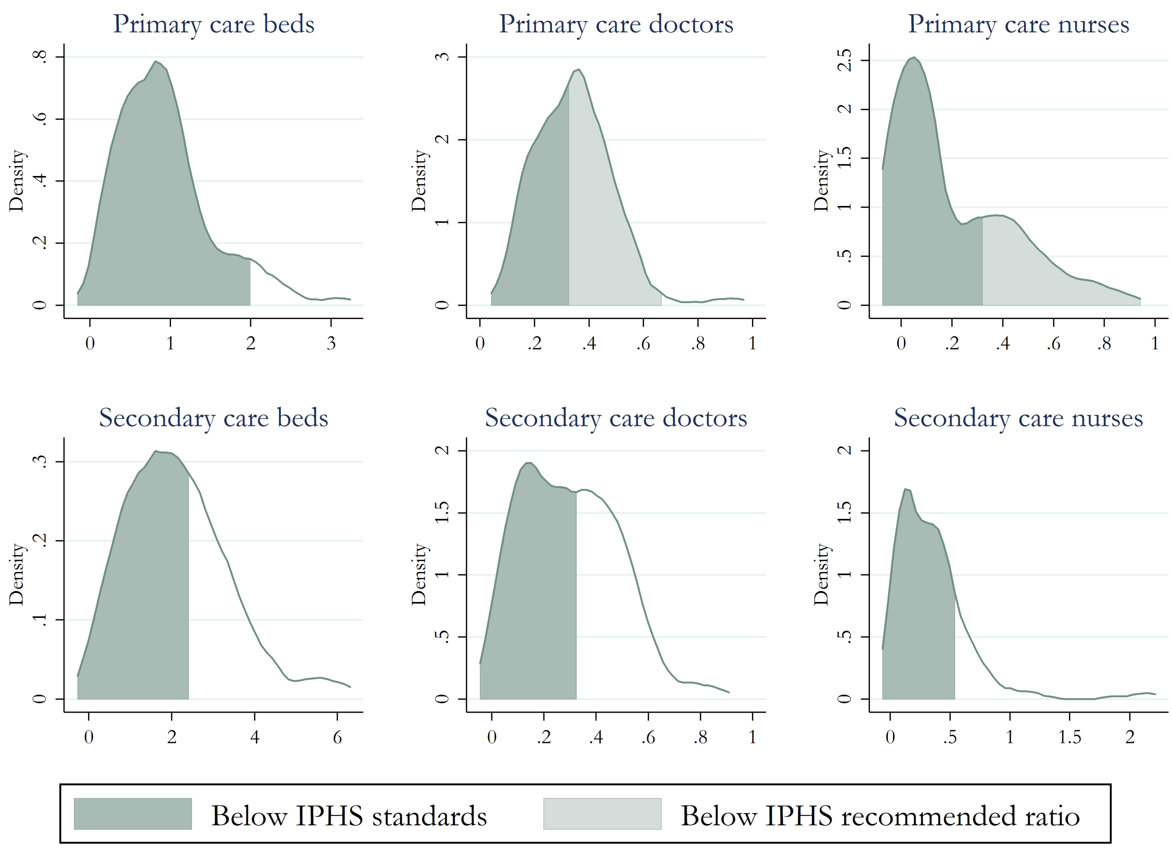
In our main analysis we simply use an indicator of whether the district had above- or below-median pre-existing capacity in the primary and/or secondary system based on these

[14]The survey focused on districts that had not been covered by the earlier DLHS-I facility survey

[15]It covered all primary health centers (PHCs) if the district had 30 or fewer and a random sample if the district had more.

[16]Available from: https://data.gov.in/resources/district-wise-availability-health-centres-india-sept-2004. We use 2006 data for Uttar Pradesh as 2004 data is unavailable.

Figure 1: District Health Infrastructure per 10,000 population



Notes: Figure shows kernal densiy plots of pre-existing district health infrastructure per 10,000 rural population for 170 study districts where data is available from DLHS-II facility survey. Average beds/doctors/nurses per facility estimated from DLHS-II facility survey (2002-04), number of facilities per district taken from Rural Health Statistics (2004), district (rural) population taken from 2001 census. All measures trimmed at the 99th percentile. IPHS refers to Indian Public Health Standards. For PHCs, IPHS standards are: 1 PHC per 30,000 population, 6 beds per PHC, 1 doctor per PHC (2 recommended), 1 nurse/midwife per PHC (3 recommended). For CHCs: 1 CHC per 120,000 population, 30 beds per CHC, 4 doctors per CHC, 7 nurses/midwives per CHC. (Directorate General of Health Services and Ministry of Health Family Welfare 2006; Motkuri, Vardhan, and Ahmad 2017).

Table 2: Factor analysis of District infrastructure measures

	(1) Factor	(2) Loading	(3) Factor Loading	(4) Factor Loading
PHC beds per person	0.23	0.70	0.82	
PHC doctors per person	0.07	0.73	0.88	
PHC nurses/midwives per person	-0.37	0.51	0.65	
Hospitals/CHC beds per person	0.92	0.13		0.95
Hospital doctors per person	0.89	-0.02		0.91
Hospital nurses/midwives per person	0.66	0.06		0.81
Observations	182		182	182
Eigenvalue	2.275	1.314	1.862	2.381

Notes: Table presents factor loadings for factor analysis of district-level capacity measures. Construction of measures described in section 3.2 and measures are graphed in figure 1. First two columns present rotated loadings of first two factors recovered from an exploratory factor analysis of all six capacity measures. Third and fourth columns presents first factors retained from exploratory factor analyses on measures of capacity in primary health system (third column) and secondary health system (fourth column). Number of factors retained determined by Kaiser criterion, i.e. keep all factors with eigenvalue greater than one, (Kaiser 1960).

factor measures. We use the continuous measures in robustness analysis.

3.3 JSY rollout

We estimate JSY's rollout from the DLHS-III. Each respondent was asked whether they had received a payment through JSY or another state-specific scheme for their last birth. Once JSY was rolled out in a district, all births that occurred in government institutions should have received payments. We define JSY as being active in a district from the first quarter (after its official launch) in which 25% of births that occurred in government institutions were reported to have received a JSY payment in *both* that quarter *and* the following year.[17] There is strong variation in the timing of implementation within and between states (Figure A.1). In robustness analysis, we create an alternative, fractional measure of JSY intensity – the proportion of eligible births that received the payment (see Figure A.2).

Since we hope to use the rollout of JSY to identify causal effects, we now examine how

[17] The latter condition prevents erroneous reports of respondents receiving JSY leading us to mistakenly infer a too-early start date where there are few births recorded in a district-quarter cell.

the rollout relates to longer-run trends in our outcomes of interest – perinatal mortality rates, institutional delivery rates, and vaccination rates. An association between the rollout and already-existing trends could suggest that parallel-trends assumptions required for our differences-in-differences approach to be valid might not be plausible.

To this end, we use the DLHS-II to calculate district-level changes in rates of institutional delivery, 7-day infant mortality and vaccinations between 1990 and 2001.[18] We then run district-level regressions of JSY's start date on these changes interacted with the prior capacity of the district (Table 3). Columns 1, 4, and 7 show that the start date of JSY is uncorrelated with long-run changes in the respective rates of institutional delivery, perinatal mortality, and vaccinations. The other columns of Table 3 show that the start date of JSY is correlated with capacity in the primary and secondary care sectors, but not with the interaction of pre-existing capacity with the long-run changes in institutional delivery (columns 2 and 3), perinatal mortality (columns 5 and 6), and vaccinations (columns 8 and 9). Appendix Figures A.3, A.4, and A.5 provide a more detailed study of the relationship between these prior trends and the rollout and find no evidence that that districts where JSY rolled out at different points were on different trends prior to the program.

4 JSY's Impact on Birth Outcomes

4.1 Empirical strategy

We seek to assess the causal impact of JSY on place of birth and perinatal mortality and how these impacts vary by the pre-existing capacity of the district health system. To this end, we exploit the rollout of JSY across districts between its formal launch in April 2005 and the end of 2007.

[18]DLHS-II's birth roster does not include stillbirths, so we check for parallel pre-trends only for 7-day mortality. We use "short" differences for vaccination rates (between 2001 quarter 1 and 2002 quarter 4). because the DLHS-II only contains vaccination information for a subset of recent births.

Table 3: Relation between quarter of JSY's rollout and prior trends in outcomes of interest

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
High sec. cap.		-2.991***			-2.992***			-2.486***	
		(0.392)			(0.395)			(0.530)	
High prim. cap.			1.482***			1.484***			1.485***
			(0.439)			(0.439)			(0.565)
Δ Inst. Del.	-0.0817	0.219	0.148						
	(0.189)	(0.326)	(0.379)						
High sec. cap. $\times$ Δ Inst. Del.		0.0246							
		(0.420)							
High prim. cap. $\times$ Δ Inst. Del.			0.0312						
			(0.477)						
Δ Perinatal Mort.				-0.0778	-0.136	-0.281			
				(0.189)	(0.312)	(0.333)			
High sec. cap. $\times$ Δ Peri. Mort.					0.235				
					(0.403)				
High prim. cap. $\times$ Δ Peri. Mort.						0.325			
						(0.442)			
Δ Vacc.							0.0777	0.369	0.118
							(0.238)	(0.416)	(0.408)
High sec. cap. $\times$ Δ Vacc.								-0.328	
								(0.540)	
High prim. cap. $\times$ Δ Vacc.									0.0939
									(0.569)
Observations	249	181	181	249	181	181	145	101	101

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses. Estimates from district-level regressions of the quarter that JSY started on standardized (mean 0, variance 1 across districts) changes in (i) institutional delivery rates (between 1990 and 2001), (ii) 7-day infant mortality rates (between 1990 and 2001) and vaccination rates (between 2001 quarter 1 and 2002 quarter 4). All calculated from DLHS-2.

Impacts may vary with the time JSY had been operational ("event time") if, for example, it took time for all households to hear about the scheme or if facilities adapted gradually to the new demand. For each outcome we thus begin our analysis with an event study to estimate the effect of JSY at each event-time period k. Specifically, we estimate the following linear probability model:

$$Y_{ibdt} = \alpha + \sum_{k=-9}^{9} \beta_k \mathbf{1}\{K_{ibdt} = k\} + \theta_b + \theta_d + \theta_t + \nu_{ibdt}, \tag{4.1}$$

where Y_{ibdt} denotes our outcome of interest (perinatal mortality or place of birth) for birth i, of birth order b, in district d, in quarter t. K_{ibdt} denotes the event time (in quarters) since JSY became active in district d, with $K_{ibdt} = 0$ in the quarter of initiation. θ_b , θ_d and θ_t are, respectively, birth-order, district and quarter-of-birth fixed effects. ν_{ibdt} is the error term which we allow to be arbitrarily correlated amongst births within a district over time by clustering standard errors at the district level (Bertrand, Duflo, and Mullainathan 2004).

We do not have a large "always untreated" sample as JSY had rolled out to almost all districts by the end of our sample period. Therefore, we must restrict two lags to identify the model (Borusyak and Jaravel 2017); we thus set β_{-9}, the first event period, and β_{-1}, the period immediately before JSY's rollout, to zero. The specification allows us to test for differences in non-linear pre trends – by testing the null hypothesis $H_0 : \beta_{-8} = ...\beta_{-2} = 0$ – but not for differences in the linear component of pretrends (Borusyak and Jaravel 2017). This test complements our earlier analysis, in Section 3.3, which suggested that the rollout was unrelated to longer-run trends in the outcomes of interest.

Our identifying assumption is that, conditional on district, quarter of birth and birth order, birth-specific shocks are mean independent of JSY's rollout, i.e. $\mathrm{E}[\nu_{ibdt}|\mathbf{1}\{K_{ibdt} = k\}, \theta_b, \theta_d, \theta_t, \forall k = \{-8, ... -2, 0, ..9\}] = 0$. This is a multi-period parallel trends assumption and rules out that the rollout of JSY was related to birth-specific shocks but does not rule out that the rollout was related to birth-specific gains from JSY.[19] Under this assumption, and the assumption of no systematic heterogeneity in treatment effects across cohorts (Abraham and Sun 2018), β_k identifies the average causal effect of JSY k periods after it began.

To examine dynamic treatment effects by pre-existing capacity we repeat this analysis but interact JSY's rollout with capacity indicators:

$$Y_{ibdt} = \alpha + \sum_{k=-9}^{9} \beta_k \mathbf{1}\{K_{ibdt} = k\} + \sum_{k=-9}^{9} \gamma_k C_d \mathbf{1}\{K_{ibdt} = k\} + \theta_b + \theta_d + \theta_t + \nu_{ibdt} \tag{4.2}$$

where C_d is a vector containing measures of the capacity of district d prior to the rollout and where we again impose effects at $k = -9$ and $k = -1$ to be zero. The identifying assumption here is $\mathrm{E}[\nu_{ibdt}|\mathbf{1}\{K_{ibdt} = k\}, C_d\mathbf{1}\{K_{ibdt} = k\}, \theta_b, \theta_d, \theta_t, \forall k = \{-8, ... - 2, 0, ..9\}] = 0$ and rules out that the rollout within districts with the same pre-existing capacity level was related to birth specific risks once conditioning on district, quarter of birth and birth order. In our main analysis C_d is simply a binary indicator for district d having above-average pre-existing capacity; in this case β_k represents the effect of JSY in low-capacity districts k periods after it began and $\beta_k + \gamma_k$ represents JSY's effect in high-capacity districts.

Where we fail to reject the null of no differential non-linear pre trends, we next place more structure on our analysis in order to increase precision while maintaining the ability to pick up treatment effects that vary over time. We thus, using the identical sample (i.e. $-9 \leq K_{ibdt} \leq 9$) estimate a model which allows the treatment effect associated with JSY to comprise both a level shift and a trend break:

$$Y_{ibdt} = \alpha + \beta_{shift} JSY_{dt} + \beta_{break} JSY_{dt} \times K_{ibdt} + \theta_b + \theta_d + \theta_t + \nu_{ibdt} \tag{4.3}$$

where JSY_{dt} is an indicator for whether JSY had begun in district d and quarter t, i.e.

[19] To see this, decompose ν_{ibdt} into $\sum_{k=0}^{9}(\beta_{ik} - \beta_k)\mathbf{1}\{K_{ibdt} = k\} + \epsilon_{ibdt}$ where β_k is the average effect of JSY at event time k. For $\mathrm{E}[\nu_{ibdt}|\mathbf{1}\{K_{ibdt} = k\}, \theta_b, \theta_d, \theta_t, \forall k = \{0, ..9\}] = 0$ we require $\mathrm{E}[\epsilon_{ibdt}|\mathbf{1}\{K_{ibdt} = k\}, \theta_b, \theta_d, \theta_t, \forall k = \{0, ..9\}] = 0$ but not $\mathrm{E}[\beta_{ik}|\mathbf{1}\{K_{ibdt} = k\}, \theta_b, \theta_d, \theta_t, \forall k = \{0, ..9\}] = 0$.

$JSY_{dt} = \mathbf{1}\{K_{ibdt} \geq 0\}$. As before, K_{ibdt} is quarter of birth. We estimate the identical model allowing for an interaction between treatment terms and pre-existing capacity to examine heterogeneity.

Finally, we summarize the dynamic treatment effects – estimated using specifications (4.1) and (4.2) – into a single average effect. To do so, we follow Borusyak and Jaravel (2017) and estimate a weighted average effect, $\hat{\beta}^{average}$, and corresponding standard error $\widehat{se(\hat{\beta}^{average})}$, using weights proportional to sample size at each event time:

$$\hat{\beta}^{average} = \sum_{k=0}^{9} w_k \hat{\beta}_k, \quad \widehat{se(\hat{\beta}^{average})} = \sum_{k=0}^{9} w_k \widehat{se(\hat{\beta}_k)}, \quad w_k = \frac{\sum_i \mathbf{1}\{K_{ibdt} = k\}}{\sum_{k'=0}^{9} \sum_i \mathbf{1}\{K_{ibdt} = k'\}} \tag{4.4}$$

When treatment effects vary with time, this approach is preferable to the commonly-used two-way fixed effects regression – i.e. with a treatment dummy and unit and time fixed effects – which recovers a weighted average of treatment effects that places negative weight on longer-run effects (Borusyak and Jaravel 2017). To increase precision, we estimate dynamic effects under the restriction that the coefficients on the lags of JSY's rollout, β_{-8} through β_{-2}, are zero after first testing this restriction.

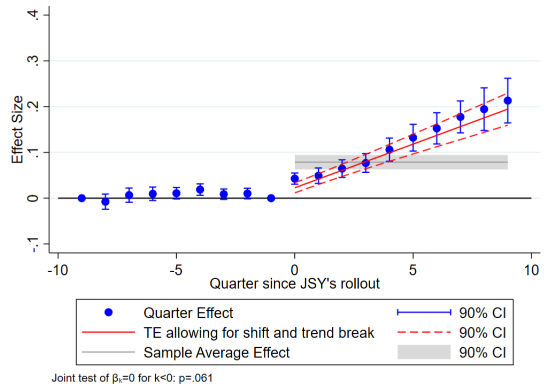
4.2 Impacts on Institutional Delivery

Our event studies – using specifications (4.1) and (4.2) – indicate that JSY led to a very substantial increase in the rate of institutional delivery and that the impact of JSY increased with the time it was operational in a district (Figure 2). The analysis suggests that after two years of operation, JSY had increased the probability that a birth took place in a medical facility by around 20 percentage points.

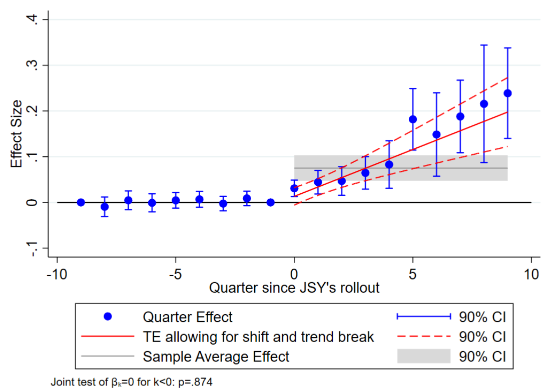
For all levels of pre-existing capacity, we cannot reject that effects prior to JSY's rollout are zero. After it's rollout, effects appear to increase with time in a roughly linear fashion, and thus the specification allowing for a level shift and trend break (in red) closely mirrors the event study (in blue). At first glance, effects do not appear to vary substantially by the

Figure 2: Effects of JSY on Institutional Delivery over Time

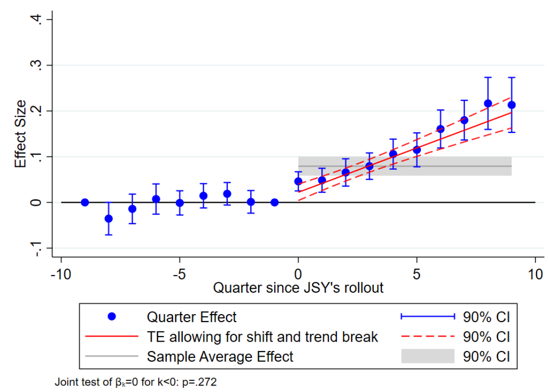
(a) Whole Sample



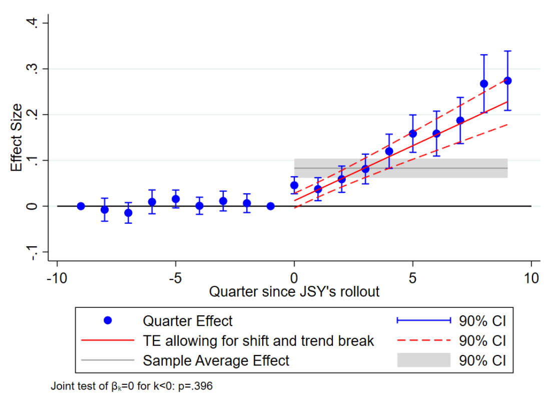
(b) Low Secondary Care Capacity



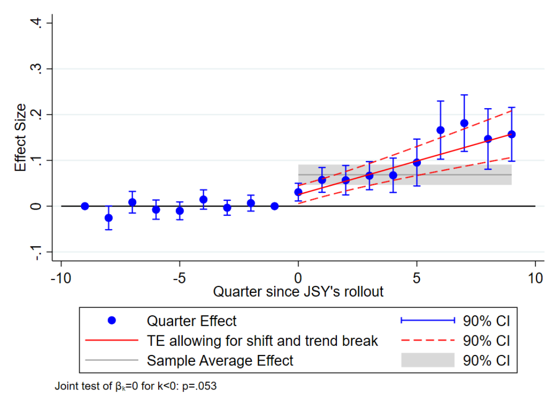
(c) High Secondary Care Capacity



(d) Low Primary Care Capacity



(e) High Primary Care Capacity



Notes: Figures plot: (1, in blue) event-time effects by pre-existing capacity from event studies described by equations (4.1) and (4.2). Specifically we plot coefficients β_k (in graphs a,b,d), $k = -9, ...9$ and $\beta_k + \gamma_k$ (in graphs c and e); (2, in red) dynamic effects allowing for JSY to cause both a level shift and a trend break as estimated from equation (4.3); (3, in grey) average effects of JSY, i.e. quarter-specific effects weighted by event-time distribution of sample according to equation (4.4).

pre-existing capacity of the district.

Next, we estimate the average of these dynamic effects, weighted according to the event-time distribution of our sample (equations (4.4)). Overall, JSY increased the average probability of institutional delivery by 7.86 percentage points ($p < 0.001$), or 35% of the mean before the policy's launch, across all sample districts (Table 4, column 1) and 7.62 percentage points across districts with capacity data available (column 2). As we saw from the event study, the increase appears similar in districts with more and with less capacity prior to the rollout (columns 3-5). These effect sizes are in line with those found by Powell-Jackson, Mazumdar, and Mills (2015).

Breaking this down into different types of institutional deliveries, we see that this increase was comprised of an increase of 6.30 percentage points ($p < 0.001$) in the probability of births occurring in government-run secondary care facilities, an increase of 3.14 percentage points ($p < 0.001$) for government-run primary care facilities and a decrease of 1.58 percentage points ($p = 0.003$) for private facilities (in most states payments were not given for births in private facilities) (Table 5).

The magnitudes of these increases are large relative to the prior rate of institutional delivery and the capacity of the government health system. A back-of-the-envelope calculation suggests that an increase in the proportion of births occurring in government facilities (secondary and primary) of 9.44 percentage points (Table 5) translates into an increase in the average number of births per day occurring in each government-run secondary care facility, or in a primary care facility under the supervision of that secondary facility, from 1.73 prior to JSY to 3.59 afterwards. Even though the increase in institutional delivery was the same across districts with more and with less capacity in the secondary care system, the difference in the number of facilities means the increase in caseload was much more pronounced in districts with low pre-existing secondary care capacity (from 1.92 to 4.80) than with higher capacity (1.54 to 2.38).[20]

[20] Taking India's 2005 crude birth rate of 24.2 per thousand people (from data.worldbank.org) we estimate the number of births per day in each district using population figures from the 2001 census. We then estimate

Table 4: Effect of JSY on Institutional Delivery by Pre-Existing Capacity

	(1)	(2)	(3)	(4)	(5)
JSY	0.0786***	0.0762***	0.0769***	0.0830***	0.0748***
	(0.0095)	(0.0114)	(0.0170)	(0.0127)	(0.0181)
JSY x High secondary cap.			0.0018		0.0183
			(0.0170)		(0.0208)
JSY x High primary cap.				-0.0143	0.0152
				(0.0143)	(0.0239)
JSY x High sec. cap. X High prim. cap.					-0.0433
					(0.0313)
Observations	81242	59901	59901	59901	59901
Number of districts	256	182	182	182	182
Mean Prior to 2005Q2	0.2240	0.2260	0.2260	0.2260	0.2260

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses. Effects are weighted (weights proportional to sample size, defined in (4.4))) averages of dynamic effects (estimated using specifications (4.1) and (4.2)). All estimates control for quarter-of-birth, birth-order and district fixed effects. Standard errors are clustered at the district level. First column includes data for all sample districts. The remaining columns include data only for districts with capacity data available. High secondary cap. (High primary sec.) is an indicator taking the value 1 if district has above-median secondary (primary) care capacity, as defined in section 3.2.

Table 5: Effect of JSY on Place of Birth

	Panel A: All Government Facilities			*Panel B: Gov. Secondary Care*		
	(1)	(2)	(3)	(4)	(5)	(6)
JSY	0.0944***	0.0996***	0.0985***	0.0630***	0.0478***	0.0749***
	(0.0084)	(0.0177)	(0.0119)	(0.0064)	(0.0118)	(0.0090)
JSY x High secondary cap.		-0.0020			0.0287**	
		(0.0186)			(0.0124)	
JSY x High primary cap.			-0.0046			-0.0201**
			(0.0157)			(0.0098)
Observations	81242	59901	59901	81242	59901	59901
Number of districts	256	182	182	256	182	182
Mean Prior to 2005Q2	0.1552	0.1573	0.1573	0.1131	0.1133	0.1133

	Panel C: Gov. Primary Care			*Panel D: Private Facility*		
	(7)	(8)	(9)	(10)	(11)	(12)
JSY	0.0314***	0.0518***	0.0236***	-0.0158***	-0.0227***	-0.0156**
	(0.0046)	(0.0110)	(0.0069)	(0.0053)	(0.0078)	(0.0063)
JSY x High secondary cap.		-0.0307***			0.0038	
		(0.0111)			(0.0070)	
JSY x High primary cap.			0.0155			-0.0097
			(0.0104)			(0.0063)
Observations	81242	59901	59901	81242	59901	59901
Number of districts	256	182	182	256	182	182
Mean Prior to 2005Q2	0.0421	0.0440	0.0440	0.0687	0.0686	0.0686

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses. Effects are weighted (weights proportional to sample size, defined in (4.4))) averages of dynamic effects (estimated using specifications (4.1) and (4.2)). All estimates control for quarter-of-birth, birth-order and district fixed effects. Standard errors are clustered at the district level. High secondary cap. (High primary sec.) is an indicator taking the value 1 if the district has above-median secondary (primary) care capacity, as defined in section 3.2.

Table 6: Effect of JSY on Perinatal Mortality by Pre-Existing Capacity

	(1)	(2)	(3)	(4)	(5)
JSY	0.0015	0.0032	0.0090**	0.0048	0.0111**
	(0.0027)	(0.0033)	(0.0039)	(0.0038)	(0.0044)
JSY x High secondary cap.			-0.0082**		-0.0117**
			(0.0035)		(0.0052)
JSY x High primary cap.				-0.0043	-0.0040
				(0.0034)	(0.0041)
JSY x High sec. cap. X High prim. cap.					0.0061
					(0.0063)
Observations	104057	76804	76804	76804	76804
Number of districts	256	182	182	182	182
Mean Prior to 2005Q2	0.0347	0.0370	0.0370	0.0370	0.0370

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses. Effects are weighted (weights proportional to sample size, defined in (4.4))) averages of dynamic effects (estimated using specifications (4.1) and (4.2)). All estimates control for quarter-of-birth, birth-order and district fixed effects. Standard errors are clustered at the district level. First column includes data for all sample districts. The remaining columns include data only for districts with capacity data available. High secondary cap. (High primary sec.) is an indicator taking the value 1 if district has above-median secondary (primary) care capacity, as defined in section 3.2.

4.3 Impacts on Perinatal Mortality

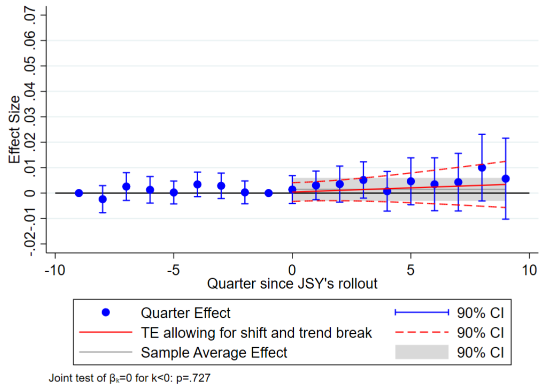
We now move on to assess impacts on perinatal mortality. In line with Powell-Jackson, Mazumdar, and Mills (2015) we find that the average effect, across districts with high and low pre-existing capacity, of JSY is close to zero and not statistically significant; this holds both in terms of the dynamic effects (Figure 3(a)) and when averaged over event time (Table 6, columns 1 and 2).

However, the results are markedly different in districts with below-median pre-existing capacity in the secondary healthcare system from districts with above-median capacity. In the former, low-capacity districts, Figure 3 shows that JSY increased the risk of perinatal

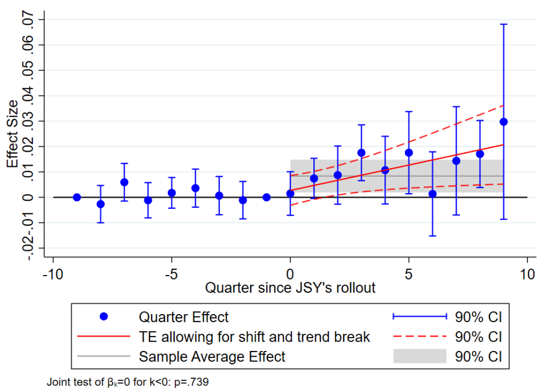
the average number taking place each day in government health facilities both before JSY's rollout (using the observed rate in the district before JSY) and after (using this baseline rate plus 0.0944). We finally divide these figures by the number of secondary care facilities in the district.

Figure 3: Effects of JSY on Perinatal Mortality over Time

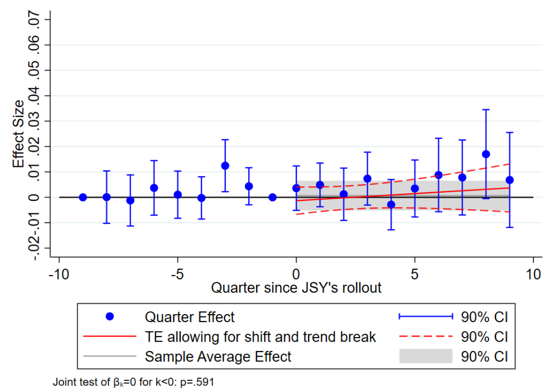
(a) Whole Sample



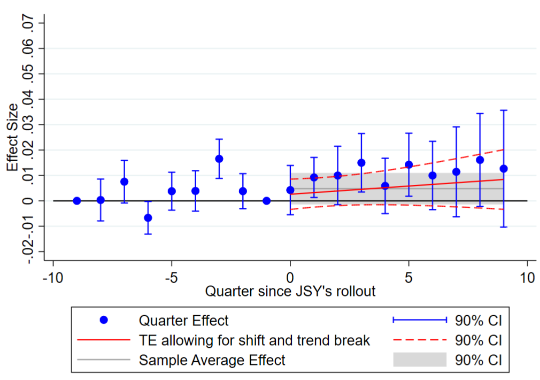
(b) Low Secondary Care Capacity



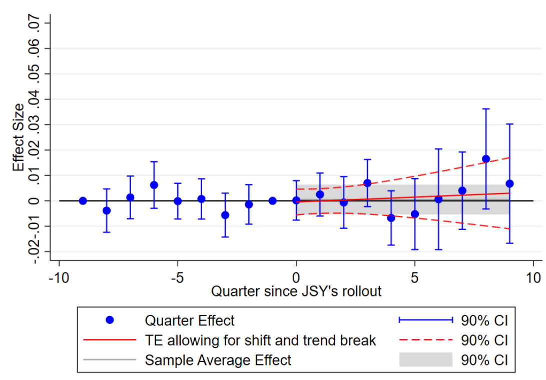
(c) High Secondary Care Capacity



(d) Low Primary Care Capacity



(e) High Primary Care Capacity



Notes: Figures plot: (1, in blue) event-time effects by pre-existing capacity from event studies described by equations (4.1) and (4.2). Specifically we plot coefficients β_k (in graphs a,b,d), $k = -9, ...9$ and $\beta_k + \gamma_k$ (in graphs c and e); (2, in red) dynamic effects allowing for JSY to cause both a level shift and a trend break as estimated from equation (4.3); (3, in grey) average effects of JSY, i.e. quarter-specific effects weighted by event-time distribution of sample according to equation (4.4).

mortality with effects growing somewhat in magnitude over time. The average impact across event times (Table 6, column 3) is an increase in the risk of perinatal mortality of 0.90 percentage points ($p = 0.020$). In districts with above-median secondary capacity, on the other hand, JSY had no impact at any event time or averaged across event times ($p = 0.811$), with the difference in the average effect between these above-median capacity districts and the districts with low capacity being statistically significant ($p = 0.022$). These magnitudes are substantial when compared to the rate of perinatal mortality of 3.70% in the 15 months before JSY's launch.

Although point estimates for the effect of JSY of perinatal mortality in districts with low primary care capacity are positive (an increase in mortality risk), these are not statistically significant either over time (Figure 3) or on average (Table 6), column 4 and 5). And neither is the difference in effects between districts with high and low primary care capacity.

4.4 Mechanisms

We consider it plausible that JSY affected the risk of perinatal mortality in each district through two distinct channels. First, we have shown that JSY caused births that would otherwise have occurred at home to instead occur in health facilities. Call these births complier births. If the risk of perinatal mortality for complier births differed by whether or not they occurred in a facility, then JSY will have changed the perinatal mortality rate. Second, the increase in the number of births occurring in facilities may have affected the quality of care they provided, both to complier births and to births that would occur in facilities regardless of JSY (which we term always-taker births). In appendix A.2 we use a potential outcomes framework to decompose the average causal effect (ACE) of JSY on the risk of perinatal mortality under two assumptions: (i) that JSY did not affect the riskiness of a given birth occurring at home and (ii) did not cause any births to move from facilities into the home (akin to a no defiers assumption). We show that under these assumptions, the ACE of JSY on perinatal mortality can be decomposed into the weighted average of three

ACEs:[21]

$$\begin{aligned} \beta =&\pi_c \left[\text{ACE of inst. delivery (in absence of JSY) on mortality for } \textit{complier} \text{ births}\right] \\ &+ \pi_c \left[\text{ACE of JSY on mortality associated with inst. delivery for } \textit{complier} \text{ births}\right] \\ &+ \pi_a \left[\text{ACE of JSY on mortality associated with inst. delivery for } \textit{always-taker} \text{ births}\right] \end{aligned} \tag{4.5}$$

where π_c and π_a are the proportions of complier and always-taker births. The element in brackets in the first line of (4.5) represents the effect on mortality of delivering in a facility versus at home for complier births if JSY did not affect in-facility perinatal mortality risk (i.e. if JSY did not change the quality of care in health care facilities). The terms in the second and third lines represent the effect of JSY on mortality due to its effect on the quality of care.

We consider a simple bounding exercise to argue that some portion of the detrimental impact of JSY on mortality risk in low secondary capacity areas likely comes from JSY changing the quality of institutional delivery, i.e. changing the mortality risk associated with institutional delivery. If we shut down this channel, this sets the last two lines of equation (4.5) to zero. We estimated that the average effect of JSY on perinatal mortality in areas with low secondary care capacity was 0.9 percentage points, while the average effect on institutional delivery, aka the number of compliers, in these areas was 7.69 percentage points. Therefore, shutting down the impact of JSY on the quality of institutional delivery, we would have to attribute this 0.9 percentage point increase in mortality entirely to these births, implying that the average causal effect of institutional delivery for complier births must be a risk of 11.7 percent (0.9 p.p./7.69 p.p.). This is implausibly large given a baseline mortality risk of 3.7 percent. We thus conclude that some portion of the mortality increase came from an increased risk for always-taker births.

[21] As shown in Table 5 we find substantial net movements from both home delivery and private facilities to government-run institutions. However, we cannot explicitly test a "no defiers" assumption. Appendix A.2 decomposes the treatment effect in the presence of defiers.

5 JSY's Impact on Vaccination Rates

We employ the same empirical strategy to examine spillover impacts of JSY on another service that the local health system performs: childhood vaccinations. Our outcome here is the proportion of vaccinations a child has received of those that a child her age should have received.

The examination of the dynamic effects of JSY in Figure 4 (both the event study and allowing for a shift and trend break) suggest that JSY decreased the rate of childhood vaccinations and that this decrease may have become more severe with time. When we take an average across the event time, we find that the average reduction in the proportion of the recommended vaccinations that children aged 9 months or older had received by 2.05 percentage points ($p = 0.007$). Breaking this down by the six non-polio recommended vaccinations, we find that JSY significantly reduced the probability that children received four of these recommended vaccinations. Average effect sizes vary from 1.35 percentage points for the first Diphtheria-Tetanus-Pertussis vaccine due at 1.5 months to 3.23 percentage points for the measles vaccine due at 9 months (Table 7).

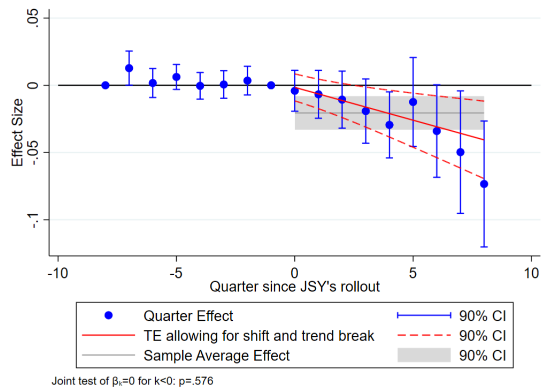
Reductions in vaccination rates do not vary with pre-existing capacity (Figure 4, Table A.1). One reason why heterogeneity in effects might not mirror that found for perinatal mortality is that in areas with lower secondary care capacity roughly one half of the increase in institutional delivery came through primary care facilities (Table 5). This increase in the use of primary care facilities for deliveries might have mitigated some of the detrimental effects of JSY on vaccination rates if giving birth there meant local health professionals could follow up more easily with the parents on the child's vaccinations.

6 Robustness

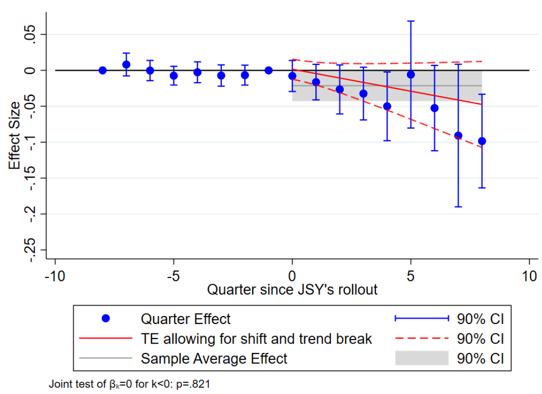
In the appendix we show results using a static specification, i.e. $Y_{ibdt} = \alpha + \beta \mathbf{1}\{K_{ibdt} \geq 0\} + \theta_b + \theta_d + \theta_t + \nu_{ibdt}$. Effect sizes for perinatal mortality (Table A.2) and vaccinations

Figure 4: Effects of JSY on Vaccination Rates over Time

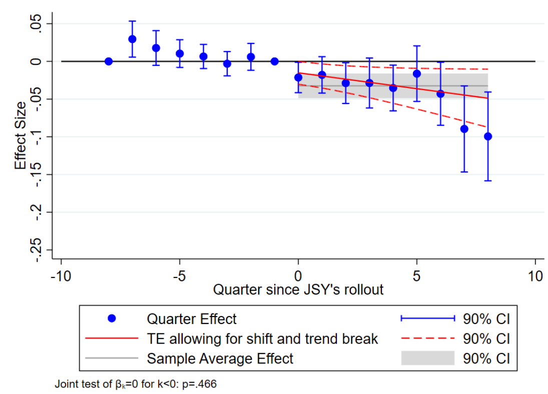
(a) Whole Sample



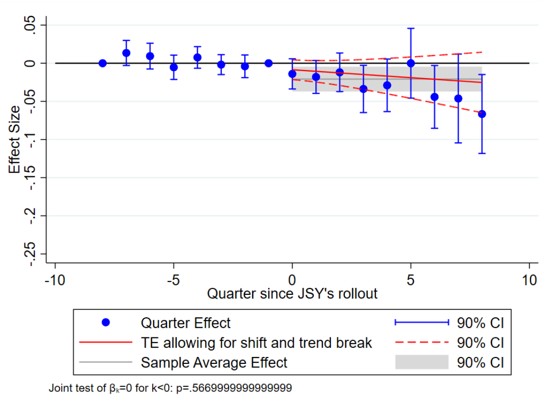
(b) Low Secondary Care Capacity



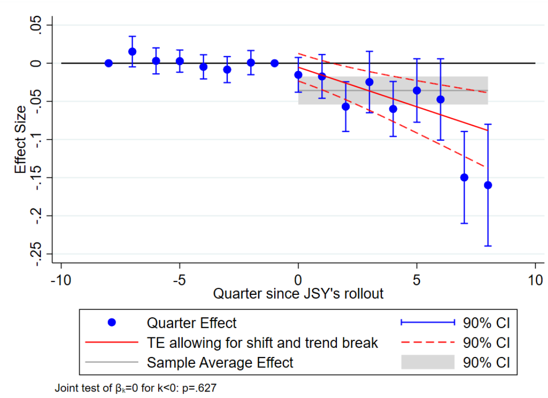
(c) High Secondary Care Capacity



(d) Low Primary Care Capacity



(e) High Primary Care Capacity



Notes: Figures plot: (1, in blue) event-time effects by pre-existing capacity from event studies described by equations (4.1) and (4.2). Specifically we plot coefficients β_k (in graphs a,b,d), $k = -9, ...9$ and $\beta_k + \gamma_k$ (in graphs c and e); (2, in red) dynamic effects allowing for JSY to cause both a level shift and a trend break as estimated from equation (4.3); (3, in grey) average effects of JSY, i.e. quarter-specific effects weighted by event-time distribution of sample according to equation (4.4).

Table 7: Effect of JSY on Vaccination Rates

	(1) Mean	(2) BCG	(3) DPT-1	(4) DPT-2	(5) DPT-3	(6) Measles	(7) Vitamin A
JSY	-0.0205***	-0.00818	-0.0135*	-0.0115	-0.0311***	-0.0323***	-0.0225**
	(0.00757)	(0.00741)	(0.00804)	(0.00992)	(0.0109)	(0.00908)	(0.00920)
Observations	79298	96284	95886	95175	93894	79298	79298
Administration age (months)		0	1.5	2.5	3.5	9	9
Mean Prior to 2005Q2	0.639	0.786	0.717	0.614	0.510	0.648	0.557

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses. Effects are weighted (weights proportional to sample size, defined in (4.4))) averages of dynamic effects (estimated using specification (4.1)). All estimates control for quarter-of-birth, birth-order and district fixed effects. Standard errors are clustered at the district level. One column per vaccination. Sample for each regression include all children who are older than the recommended age of administration for that vaccination. Sample for the mean coverage rate (column 1) includes only children older than 9 months who should have received all vaccinations.

(Table A.3) are nearly identical to the weighted average of the dynamic effects which is unsurprising as the dynamic effects do not vary substantially with time (Figures 3 and 4). For institutional delivery the static specification produces smaller, but still highly statistically significant, estimates (Table A.4) which is expected given, as shown in Figure 2, the dynamic effects increase with time (Borusyak and Jaravel 2017).

Non-random attrition is a potential concern for our analysis of the effects of JSY on vaccination rates since JSY affected perinatal mortality and thus, presumably, the probability of births having complete vaccination data. Since such attrition is unlikely to be monotonic with respect to JSY, rendering Lee bounds (Lee 2009) inappropriate, we calculate the upper bound on the vaccination effect under different "worst-case" assumptions about the (counterfactual) vaccination rates for non-surviving births before versus after JSY (see Appendix A.3). We show that the difference in these rates would have to be extreme for the upper-bound to become non-negative. For example, for a vaccination rate of 80% for non-surviving births after JSY, the corresponding rate before JSY would have to be 20% to overturn the negative effect. This difference dwarfs differences in coverage rates along observables; for example, the difference between children of mothers who have ever vs. never attended school is 21% (77% vs. 56%). We thus consider it implausible that potential outcomes of non-surviving births would differ enough to drive our finding that JSY reduced vaccination rates.[22]

We further show that results are robust to using a probit model (Tables A.5, A.6, A.7) and to using a fractional indicator of JSY intensity (Table A.8, A.9, A.10). Heterogeneity results are robust to using continuous measures of pre-existing capacity (Tables A.11, A.12) and to allowing for differential time trends by pre-existing capacity (Tables A.13, A.14).

7 Interpretation and Discussion

We show that stimulating demand without simultaneously addressing supply in an under-resourced health system where poor-quality care is common can be harmful. The impact of JSY on the caseload that local health systems were expected to manage was large; JSY doubled the number of institutional births that each secondary health facility was responsible for and multiplied this number by 2.5 in areas with below-median numbers of beds, doctors and nurses in the secondary care system. In these low-capacity districts, JSY increased the perinatal mortality rate by an average of 0.90 percentage points, or by 24.3% relative to the rate before JSY's launch. We show that under all reasonable assumptions about the relative mortality risks associated with home vs. institutional birth for compliers, at least some of the overall increase in mortality must be due to lower quality of care as a result of JSY. What's more, we found the adverse consequences were not confined to birth outcomes: JSY led to a reduction in children being up to date with routine vaccinations by an average of 2.05 percentage points.

The results suggest that the existing capacity and quality of a health system should be paramount in policy decisions about whether and how to stimulate demand. This is particularly the case for risky health interventions, such as institutional delivery. While simple procedures carried out during institutional delivery can save lives (Lawn et al. 2005),

[22]This is especially likely when we consider that most non-surviving births would not have survived regardless of whether or not JSY was active.

institutional delivery brings new risks, especially if staff are overstretched, the facility is overcrowded, and if cleanliness guidelines are not followed (Fink et al. 2015; Bhutta et al. 2014; Gon et al. 2017). In an Indian context, a recent study of operating theaters, labor rooms and medical wards in New Delhi found 10% of samples were contaminated with dangerous pathogens (Dadhich et al. 2014). Thus the effects of stimulating demand for invasive interventions might depend far more on the quality of health providers than stimulating demand for less invasive interventions like vaccinations or nutritional education that are unlikely to be harmful. This implies that the moderately positive health benefits from CCTs that incentivized non-invasive health interventions (Lagarde et al. 2009; Attanasio et al. 2005; Gertler 2004; Maluccio and Flores 2005; Morris et al. 2004; Rivera et al. 2004; Behrman and Hoddinott 2005) might not carry over to more invasive procedures.

Nothing in the design of JSY helped pregnant women assess the quality of the healthcare that institutions provided or negotiate for better quality care. While recent work has highlighted that patients' healthcare choices are somewhat responsive to quality (Chandra et al. 2016; Gaynor et al. 2016; Pope 2009; Das et al. 2016; Wiseman et al. 2008; Sahn et al. 2003), the difficulty of discerning and reacting to quality remains a fundamental barrier to individuals seeking out the optimal amount of quality care (Arrow 1963; Skinner 2011; Garber and Skinner 2008; Björkman and Svensson 2009; Nyqvist et al. 2017). The more difficult it is for potential patients to discern and act upon quality, the higher the stakes of demand-side policies like JSY are since choices will be more responsive to incentives. The ASHAs who are JSY's intermediaries between mothers and the health system receive monetary incentives for each institutional delivery they register. They thus face few incentives to inform pregnant women about the poor quality of some facilities or to hold facilities accountable for poor quality care. This contrasts with many Latin American CCTs where intermediaries are elected representatives of beneficiaries and may be more prosocially motivated and better able to hold health providers to account (Barber and Gertler 2010).

ASHAs are incentivized to create demand both for institutional delivery and for childhood vaccinations. We cannot identify what portion of the detrimental impacts of JSY on vaccination coverage arise from a substitution of effort and resources by health centers away from activities related to the Universal Immunization Program towards institutional deliveries and what portion comes from a substitution of effort by ASHAs away from creating demand for vaccinations towards creating demand for institutional deliveries. However, since ASHAs are part of the local health system we interpret both explanations as a substitution of resources and effort away from the provision of vaccinations due to JSY.

The detrimental effects of JSY we document in this paper are short term, and in the longer run the health system might adapt to mitigate some of these problems. However, we consider this unlikely without substantial improvement to the supply side.

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A.1 Additional Tables and Figures

Table A.1: Effect of JSY on Vaccinations (Mean Rate) by Pre-Existing Capacity

	(1)	(2)	(3)	(4)	(5)
JSY	-0.0205***	-0.0270***	-0.0173	-0.0208**	-0.0183
	(0.0076)	(0.0094)	(0.0130)	(0.0098)	(0.0140)
JSY x High secondary cap.			-0.0156		-0.0050
			(0.0117)		(0.0143)
JSY x High primary cap.				-0.0149	-0.0014
				(0.0105)	(0.0160)
JSY x High sec. cap. X High prim. cap.					-0.0199
					(0.0196)
Observations	79298	57768	57768	57768	57768
Number of districts	256	182	182	182	182
Mean Prior to 2005Q2	0.6388	0.6325	0.6325	0.6325	0.6325

Notes: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Standard errors in parentheses. Effects are weighted (weights proportional to sample size, defined in (4.4))) averages of dynamic effects (estimated using specifications (4.1) and (4.2)). All estimates control for quarter-of-birth, birth-order and district fixed effects. Standard errors are clustered at the district level. First column includes data for all sample districts. The remaining columns include data only for districts with capacity data available. High secondary cap. (High primary sec.) is an indicator taking the value 1 if district has above-median secondary (primary) care capacity, as defined in section 3.2. Dependent variable is proportion of vaccinations a child is up to date with and defined for children 9 months or older who should have completed all vaccinations.

Table A.2: Effect of JSY on Perinatal Mortality by Pre-Existing Capacity (Static Specification)

	(1)	(2)	(3)	(4)	(5)
JSY=1	0.0014	0.0030	0.0073**	0.0053*	0.0113***
	(0.0022)	(0.0026)	(0.0033)	(0.0028)	(0.0034)
JSY=1 × High secondary cap.			-0.0086**		-0.0125***
			(0.0034)		(0.0040)
JSY=1 × High primary cap.				-0.0050	-0.0090**
				(0.0032)	(0.0044)
JSY=1 × High secondary cap. × High primary cap.					0.0089
					(0.0063)
Observations	104057	76804	76804	76804	76804
Number of districts	256	182	182	182	182
Mean Prior to 2005Q2	.0347	.037	.037	.037	.037

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses. Esimates use 'static' specification, i.e. $Y_{ibdt} = \alpha + \beta \mathbf{1}\{K_{ibdt} \geq 0\} + \gamma C_d \mathbf{1}\{K_{ibdt} \geq 0\} + \theta_b + \theta_d + \theta_t + \nu_{ibdt}$. All estimates control for quarter-of-birth, birth-order and district fixed effects. Standard errors are clustered at the district level. First column includes data for all sample districts. The remaining columns include data only for districts with capacity data available. JSY is an indicator taking the value 1 if JSY had rolled out by in district by time of birth. High secondary cap. (High primary sec.) is an indicator taking the value 1 if district has above-median secondary (primary) care capacity, as defined in section 3.2.

Table A.3: Effect of JSY on Vaccinations (Mean Rate) (Static Specification)

	(1) Mean	(2) BCG	(3) DPT-1	(4) DPT-2	(5) DPT-3	(6) Measles	(7) Vitamin A
JSY=1	-0.0213***	-0.0128**	-0.0120**	-0.00581	-0.0160**	-0.0308***	-0.0282***
	(0.00571)	(0.00504)	(0.00558)	(0.00631)	(0.00692)	(0.00723)	(0.00696)
Observations	93360	110922	110500	109743	108361	93360	93360
Administration age (months)		0	1.500	2.500	3.500	9	9
Mean Prior to 2005Q2	0.596	0.747	0.677	0.575	0.470	0.596	0.509

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses. Esimates use 'static' specification, i.e. $Y_{ibdt} = \alpha + \beta \mathbf{1}\{K_{ibdt} \geq 0\} + \theta_b + \theta_d + \theta_t + \nu_{ibdt}$. All estimates control for quarter-of-birth, birth-order and district fixed effects. Standard errors are clustered at the district level. JSY is an indicator taking the value 1 if JSY had rolled out by in district by time of birth.

Table A.4: Effect of JSY on Institutional Delivery by Pre-Existing Capacity (Static Specification)

	(1)	(2)	(3)	(4)	(5)
JSY=1	0.0287***	0.0256***	0.0063	0.0342***	0.0112
	(0.0075)	(0.0092)	(0.0121)	(0.0123)	(0.0167)
JSY=1 × High secondary cap.			0.0403***		0.0500**
			(0.0153)		(0.0229)
JSY=1 × High primary cap.				-0.0182	-0.0110
				(0.0154)	(0.0202)
JSY=1 × High secondary cap. × High primary cap.					-0.0188
					(0.0299)
Observations	88263	65373	65373	65373	65373
Number of districts	256	182	182	182	182
Mean Prior to 2005Q2	.193	.1943	.1943	.1943	.1943

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses. Estimates use 'static' specification, i.e. $Y_{ibdt} = \alpha + \beta \mathbf{1}\{K_{ibdt} \geq 0\} + \gamma C_d \mathbf{1}\{K_{ibdt} \geq 0\} + \theta_b + \theta_d + \theta_t + \nu_{ibdt}$. All estimates control for quarter-of-birth, birth-order and district fixed effects. Standard errors are clustered at the district level. First column includes data for all sample districts. The remaining columns include data only for districts with capacity data available. JSY is an indicator taking the value 1 if JSY had rolled out by in district by time of birth. High secondary cap. (High primary sec.) is an indicator taking the value 1 if district has above-median secondary (primary) care capacity, as defined in section 3.2.

Table A.5: Effect of JSY on Perinatal Mortality by Pre-Existing Capacity (Probit Estimates)

	(1)	(2)	(3)	(4)	(5)
Perinatal Mortality					
JSY=1	0.0211	0.0378	0.0770**	0.0571*	0.1063***
	(0.0261)	(0.0297)	(0.0350)	(0.0311)	(0.0341)
	[0.0018]	[0.0033]	[0.0070]	[0.0051]	[0.0099]
JSY=1 × High secondary cap.			-0.0871**		-0.1157***
			(0.0390)		(0.0441)
			[-0.0078]		[-0.0107]
JSY=1 × High primary cap.				-0.0437	-0.0695
				(0.0361)	(0.0438)
				[-0.0039]	[-0.0066]
JSY=1 × High secondary cap. × High primary cap.					0.0690
					(0.0725)
					[0.0066]
Observations	103542	76586	76586	76586	76586
Number of districts	252	180	180	180	180

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses. Estimates use 'static' specification, i.e. $Y_{ibdt} = \alpha + \beta \mathbf{1}\{K_{ibdt} \geq 0\} + \gamma C_d \mathbf{1}\{K_{ibdt} \geq 0\} + \theta_b + \theta_d + \theta_t + \nu_{ibdt}$. All estimates control for quarter-of-birth, birth-order and district fixed effects. Standard errors are clustered at the district level. First column includes data for all sample districts. The remaining columns include data only for districts with capacity data available. JSY is an indicator taking the value 1 if JSY had rolled out by in district by time of birth. High secondary cap. (High primary sec.) is an indicator taking the value 1 if district has above-median secondary (primary) care capacity, as defined in section 3.2. Average marginal effects corresponding to each coefficient presented in brackets.

Table A.6: Effect of JSY on Institutional Delivery by Pre-Existing Capacity (Probit Estimates)

	(1)	(2)	(3)	(4)	(5)
Institutional Delivery					
JSY=1	0.0775***	0.0687**	0.0332	0.1121***	0.0698
	(0.0222)	(0.0270)	(0.0359)	(0.0372)	(0.0539)
	[0.0222]	[0.0197]	[0.0094]	[0.0324]	[0.0200]
JSY=1 × High secondary cap.			0.0750*		0.0914
			(0.0431)		(0.0658)
			[0.0219]		[0.0272]
JSY=1 × High primary cap.				-0.0875**	-0.0756
				(0.0436)	(0.0616)
				[-0.0255]	[-0.0216]
JSY=1 × High secondary cap. × High primary cap.					-0.0294
					(0.0845)
					[-0.0096]
Observations	88263	65373	65373	65373	65373
Number of districts	256	182	182	182	182

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses. Estimates use 'static' specification, i.e. $Y_{ibdt} = \alpha + \beta\mathbf{1}\{K_{ibdt} \geq 0\} + \gamma C_d \mathbf{1}\{K_{ibdt} \geq 0\} + \theta_b + \theta_d + \theta_t + \nu_{ibdt}$. All estimates control for quarter-of-birth, birth-order and district fixed effects. Standard errors are clustered at the district level. First column includes data for all sample districts. The remaining columns include data only for districts with capacity data available. JSY is an indicator taking the value 1 if JSY had rolled out by in district by time of birth. High secondary cap. (High primary sec.) is an indicator taking the value 1 if district has above-median secondary (primary) care capacity, as defined in section 3.2. Average marginal effects corresponding to each coefficient presented in brackets.

Table A.7: Effect of JSY on Children's Vaccinations (Probit Estimates)

	(1) BCG	(2) DPT-1	(3) DPT-2	(4) DPT-3	(5) Measles	(6) Vitamin
JSY=1	-0.0321*	-0.0321*	-0.0122	-0.0424**	-0.0917***	-0.0784***
	(0.0194)	(0.0188)	(0.0188)	(0.0196)	(0.0223)	(0.0204)
	[-0.0084]	[-0.0097]	[-0.0041]	[-0.0151]	[-0.0304]	[-0.0270]
Observations	110922	110500	109743	108361	93360	93360
Age of Administration (Months)	0	1.500	2.500	3.500	9	9
Mean Prior to 2005Q2	0.747	0.677	0.575	0.470	0.596	0.509

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses. Estimates use 'static' specification, i.e. $Y_{ibdt} = \alpha + \beta\mathbf{1}\{K_{ibdt} \geq 0\} + \theta_b + \theta_d + \theta_t + \nu_{ibdt}$. All estimates control for quarter-of-birth, birth-order and district fixed effects. Standard errors are clustered at the district level. JSY is an indicator taking the value 1 if JSY had rolled out by in district by time of birth. Average marginal effects corresponding to each coefficient presented in brackets.

Table A.8: Effect of JSY on Perinatal Mortality by Pre-Existing Capacity (Fractional JSY Intensity)

	(1)	(2)	(3)	(4)	(5)
JSY intensity	-0.00251	0.00576	0.0187*	0.00835	0.0208*
	(0.00880)	(0.00954)	(0.0106)	(0.00949)	(0.0116)
High secondary cap. × JSY intensity			-0.0167**		-0.0158
			(0.00810)		(0.0110)
High primary cap. × JSY intensity				-0.00596	-0.00486
				(0.00800)	(0.0106)
High sec. cap. × High prim. cap. × JSY intensity					-0.00185
					(0.0157)
Observations	104057	76804	76804	76804	76804
Number of districts	256	182	182	182	182

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses. JSY intensity is estimate of proportion of eligible births receiving JSY payment in the district and quarter. Construction outlined in footnote to Figure A.2. Specification is $Y_{ibdt} = \alpha + \beta JSY intensity_{dt} + \gamma C_d JSY intensity_{dt} + \theta_b + \theta_d + \theta_t + \nu_{ibdt}$. All estimates control for quarter-of-birth, birth-order and district fixed effects. Standard errors are clustered at the district level. First column includes data for all sample districts. The remaining columns include data only for districts with capacity data available. High secondary cap. (High primary sec.) is an indicator taking the value 1 if district has above-median secondary (primary) care capacity, as defined in section 3.2.

Table A.9: Effect of JSY on Institutional Delivery by Pre-Existing Capacity (Fractional JSY Intensity)

	(1)	(2)	(3)	(4)	(5)
JSY intensity	0.310***	0.308***	0.279***	0.330***	0.290***
	(0.0305)	(0.0360)	(0.0489)	(0.0381)	(0.0509)
High secondary cap. × JSY intensity			0.0362		0.0633
			(0.0347)		(0.0465)
High primary cap. × JSY intensity				-0.0520	-0.0258
				(0.0326)	(0.0509)
High secondary cap. × High primary cap. × JSY intensity					-0.0537
					(0.0651)
Observations	88263	65373	65373	65373	65373
Number of districts	256	182	182	182	182

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses. JSY intensity is estimate of proportion of eligible births receiving JSY payment in the district and quarter. Construction outlined in footnote to Figure A.2. Specification is $Y_{ibdt} = \alpha + \beta JSY intensity_{dt} + \gamma C_d JSY intensity_{dt} + \theta_b + \theta_d + \theta_t + \nu_{ibdt}$. All estimates control for quarter-of-birth, birth-order and district fixed effects. Standard errors are clustered at the district level. First column includes data for all sample districts. The remaining columns include data only for districts with capacity data available. High secondary cap. (High primary sec.) is an indicator taking the value 1 if district has above-median secondary (primary) care capacity, as defined in section 3.2.

Table A.10: Effect of JSY on Children's Vaccinations (Mean Rate) (Fractional JSY Intensity)

	(1) Mean	(2) BCG	(3) DPT-1	(4) DPT-2	(5) DPT-3	(6) Measles	(7) Vitamin A
JSY intensity	-0.182***	-0.113***	-0.152***	-0.142***	-0.178***	-0.269***	-0.244***
	(0.0307)	(0.0270)	(0.0277)	(0.0308)	(0.0350)	(0.0389)	(0.0391)
Observations	93360	110922	110500	109743	108361	93360	93360
Age of Administration (Months)		0	1.500	2.500	3.500	9	9
Mean Prior to 2005Q2	0.596	0.747	0.677	0.575	0.470	0.596	0.509

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses. JSY intensity is estimate of proportion of eligible births receiving JSY payment in the district and quarter. Construction outlined in footnote to Figure A.2. Specification is $Y_{ibdt} = \alpha + \beta JSY intensity_{dt} + \theta_b + \theta_d + \theta_t + \nu_{ibdt}$. All estimates control for quarter-of-birth, birth-order and district fixed effects. Standard errors are clustered at the district level.

Table A.11: Effect of JSY on Perinatal Mortality by Pre-Existing Capacity (Continuous Capacity Measures)

	(1)	(2)	(3)
JSY=1	0.0028	0.0028	0.0025
	(0.0025)	(0.0026)	(0.0025)
JSY=1 × Secondary cap.	-0.0046**		-0.0051***
	(0.0019)		(0.0018)
JSY=1 × Primary cap.		-0.0027*	-0.0026*
		(0.0015)	(0.0015)
JSY=1 × Primary cap. × Secondary cap.			0.0018
			(0.0016)
Observations	76804	76804	76804
Number of districts	182	182	182
Mean Prior to 2005Q2	.037	.037	.037

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses. Estimates use 'static' specification, i.e. $Y_{ibdt} = \alpha + \beta \mathbf{1}\{K_{ibdt} \geq 0\} + \gamma C_d \mathbf{1}\{K_{ibdt} \geq 0\} + \theta_b + \theta_d + \theta_t + \nu_{ibdt}$. All estimates control for quarter-of-birth, birth-order and district fixed effects. Standard errors are clustered at the district level. JSY is an indicator taking the value 1 if JSY had rolled out by in district by time of birth. Capacity measures are continuous factors (defined in section 3.2), scaled to have zero mean and unit variance.

Table A.12: Effect of JSY on Institutional Delivery by Pre-Existing Capacity (Continuous Capacity Measures)

	(1)	(2)	(3)
JSY=1	0.0276***	0.0250***	0.0272***
	(0.0092)	(0.0091)	(0.0092)
JSY=1 × Secondary cap.	0.0237***		0.0283***
	(0.0079)		(0.0083)
JSY=1 × Primary cap.		-0.0112	-0.0120
		(0.0092)	(0.0086)
JSY=1 × Primary cap. × Secondary cap.			-0.0148*
			(0.0080)
Observations	65373	65373	65373
Number of districts	182	182	182
Mean Prior to 2005Q2	.1943	.1943	.1943

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses. Estimates use 'static' specification, i.e. $Y_{ibdt} = \alpha + \beta \mathbf{1}\{K_{ibdt} \geq 0\} + \gamma C_d \mathbf{1}\{K_{ibdt} \geq 0\} + \theta_b + \theta_d + \theta_t + \nu_{ibdt}$. All estimates control for quarter-of-birth, birth-order and district fixed effects. JSY is an indicator taking the value 1 if JSY had rolled out by in district by time of birth. Standard errors are clustered at the district level. Capacity measures are continuous factors (defined in section 3.2), scaled to have zero mean and unit variance.

Table A.13: Effect of JSY on Perinatal Mortality by Pre-Existing Capacity (Differential Trends by Capacity)

	(1)	(2)	(3)
JSY	0.0119**	0.0020	0.0156**
	(0.0048)	(0.0051)	(0.0064)
JSY x High secondary cap.	-0.0175**		-0.0318***
	(0.0069)		(0.0113)
JSY x High primary cap.		0.0005	-0.0116
		(0.0068)	(0.0097)
JSY x High sec. cap. X High prim. cap.			0.0312**
			(0.0145)
Observations	76804	76804	76804
Number of districts	182	182	182
Mean Prior to 2005Q2	0.0370	0.0370	0.0370

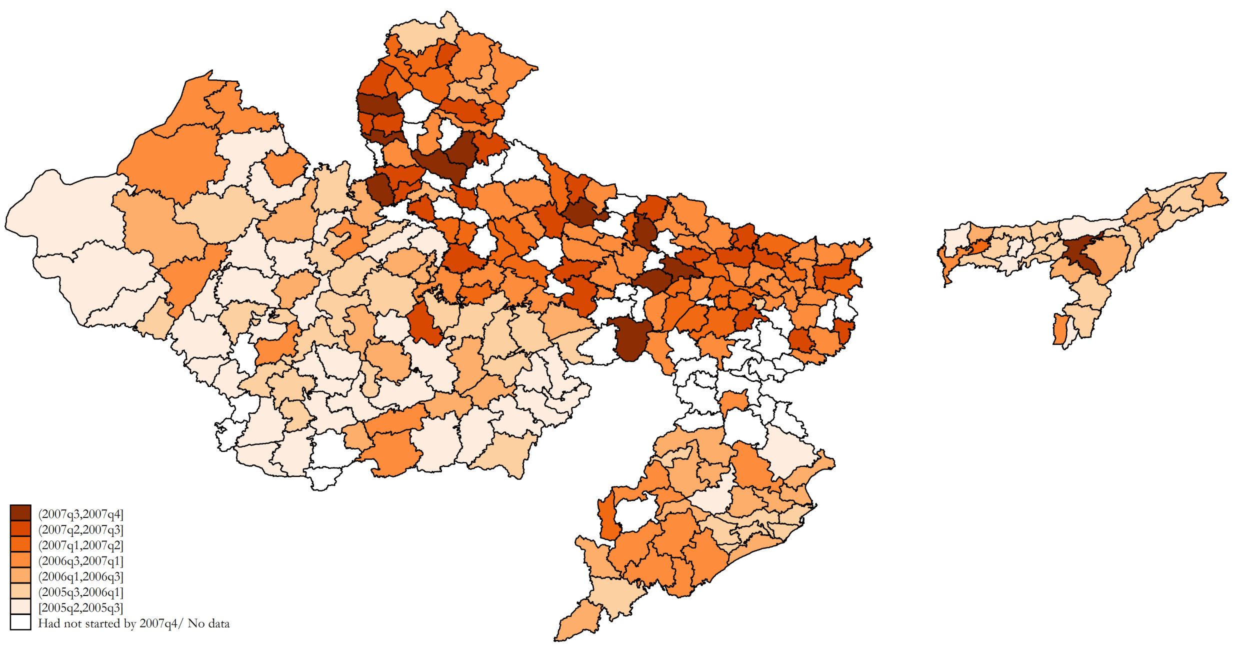
Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses. Effects are weighted (weights proportional to sample size, defined in (4.4))) averages of dynamic effects. Specification allows forpre-existing capacity specific time trends, i.e. $Y_{ibdt} = \alpha + \sum_{k=0}^{9} \beta_k \mathbf{1}\{K_{ibdt} = k\} + \sum_{k=0}^{9} \gamma_k C_d \mathbf{1}\{K_{ibdt} = k\} + \theta_b + \theta_d + C_d\theta_t + \nu_{ibdt}$. All estimates control for quarter-of-birth, birth-order and district fixed effects. Standard errors are clustered at the district level. High secondary cap. (High primary sec.) is an indicator taking the value 1 if district has above-median secondary (primary) care capacity, as defined in section 3.2.

Table A.14: Effect of JSY on Institutional Delivery by Pre-Existing Capacity (Differential Trends by Capacity)

	(1)	(2)	(3)
JSY	0.0929***	0.1058***	0.0968***
	(0.0177)	(0.0136)	(0.0225)
JSY x High secondary cap.	-0.0449*		0.0093
	(0.0245)		(0.0290)
JSY x High primary cap.		-0.0629***	0.0047
		(0.0212)	(0.0363)
JSY x High sec. cap. X High prim. cap.			-0.1145**
			(0.0460)
Observations	59901	59901	59901
Number of districts	182	182	182
Mean Prior to 2005Q2	0.2260	0.2260	0.2260

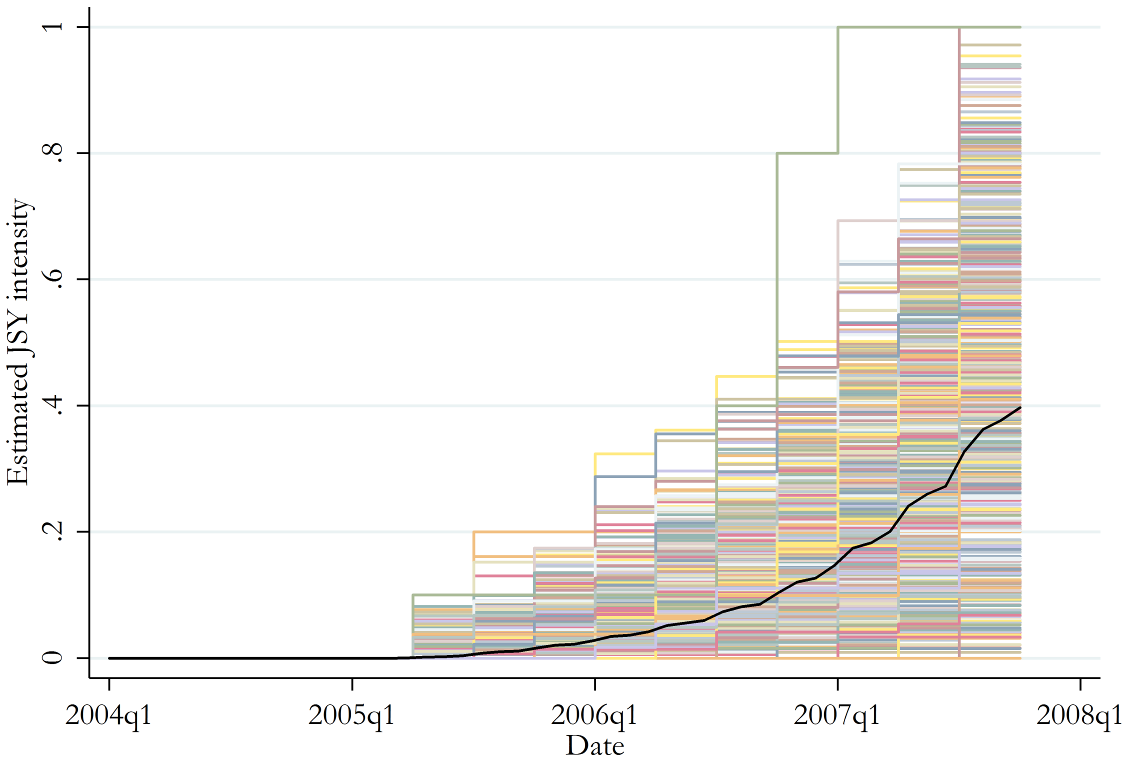
Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses. Effects are weighted (weights proportional to sample size, defined in (4.4))) averages of dynamic effects. Specification allows forpre-existing capacity specific time trends, i.e. $Y_{ibdt} = \alpha + \sum_{k=0}^{9} \beta_k \mathbf{1}\{K_{ibdt} = k\} + \sum_{k=0}^{9} \gamma_k C_d \mathbf{1}\{K_{ibdt} = k\} + \theta_b + \theta_d + C_d\theta_t + \nu_{ibdt}$. All estimates control for quarter-of-birth, birth-order and district fixed effects. Standard errors are clustered at the district level. High secondary cap. (High primary sec.) is an indicator taking the value 1 if district has above-median secondary (primary) care capacity, as defined in section 3.2.

Figure A.1: Roll-out of JSY across districts



Notes: Figure plots estimated roll-out of JSY across districts.

Figure A.2: Fractional roll-out of JSY across districts



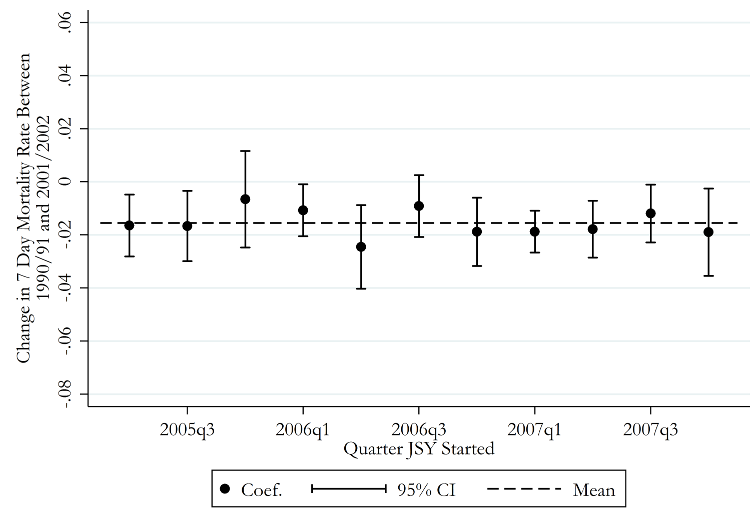
Notes: Figure plots intensity of JSY across districts over time. Intensity is defined as the proportion of births that happen in government institutions for which a JSY payment was received. Intensity is estimated using Kaplan-Meier estimate of the survivor function. Thus, for district d, in quarter t, we estimate this intensity, $J(d,t)$, as $\hat{J}(d,t) = 1 - \hat{S}(d,t)$, where $\hat{S}(d,t)$ is the nonparametric maximum likelihood estimate of the Kaplan-Meier survivor function (Kaplan and Meier 1958), defined as:

$$\hat{S}(d,t) = \prod_{j|t_j \leq t} (\frac{n_{dj} - f_{dj}}{n_{dj}})$$

where n_{dj} is the number of births occurring in government health facilities, i.e. births that are eligible for JSY, in district d in quarter j and f_{dj} is the number of these births that actually received the JSY payment.

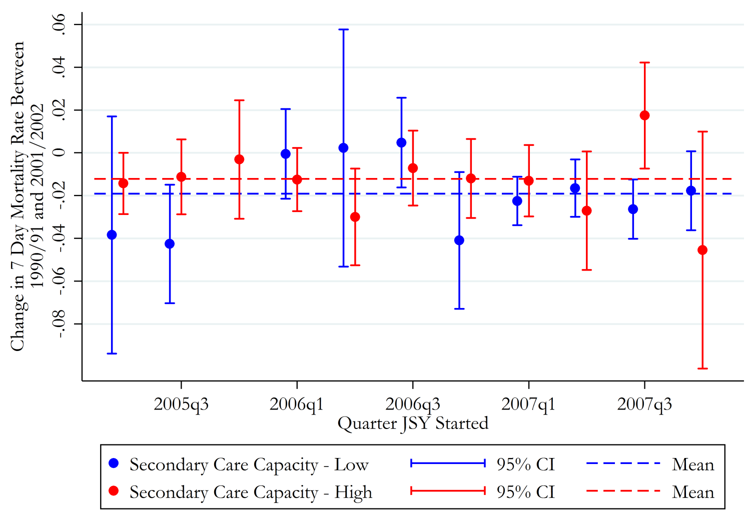
Figure A.3: Examination of parallel pre-trends in 7 day infant mortality by JSY rollout

(a) All districts



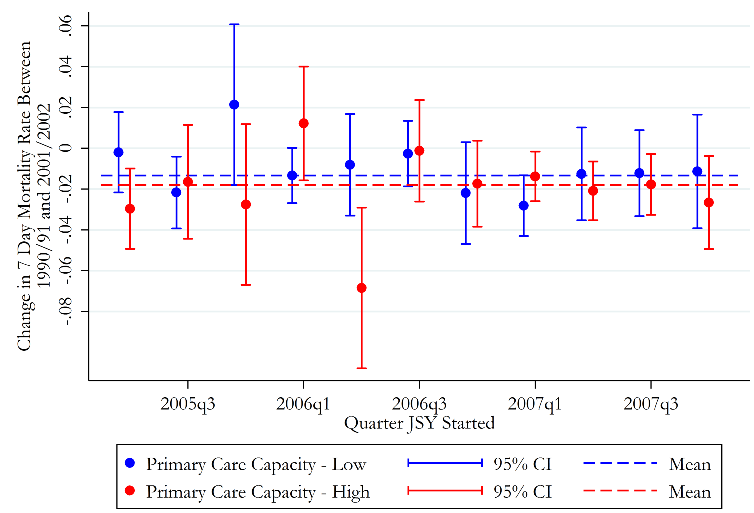
P-value for null hypothesis that all coeficients are equal =.933

(b) By Secondary Care Capacity



P-value for null hypothesis that all coeficients are equal =.425

(c) By Primary Care Capacity

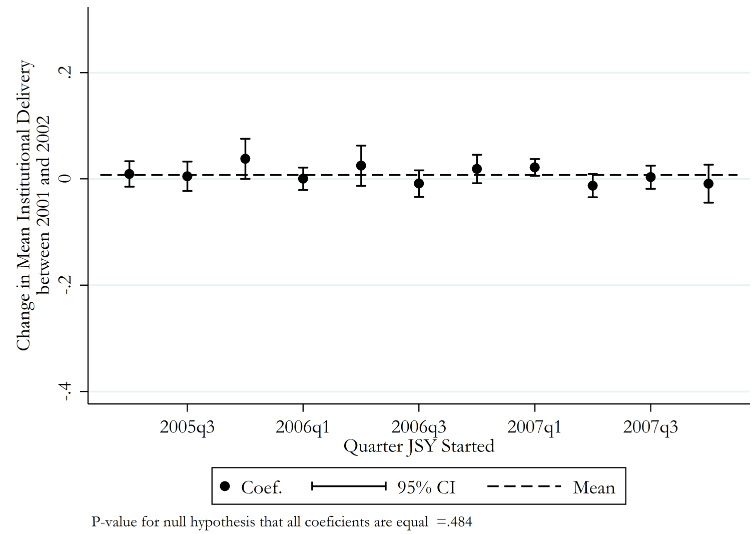


P-value for null hypothesis that all coeficients are equal =.538

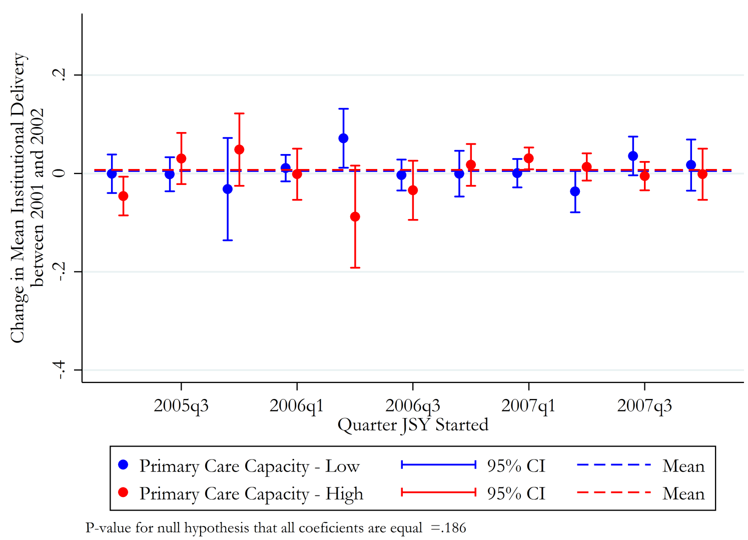
Notes: Figures plot regression coefficients and 95% confidence intervals from district level regressions of 'long differences' in perinatal mortality between 1990 and 2001 (estimated from DLHS-II) on (a) the quarter when JSY started and (b,c) the quarter when JSY started fully interacted with indicators of whether pre-existing capacity in the primary and secondary healthcare system was above or below the median. Regressions omit the constant term. We drop districts with fewer than 100 observations. The dashed lines show average coefficients across all quarters. *p*-values for testing the null hypothesis that all coefficients are equal printed below.

Figure A.4: Examination of parallel pre-trends in Institutional Delivery by JSY rollout

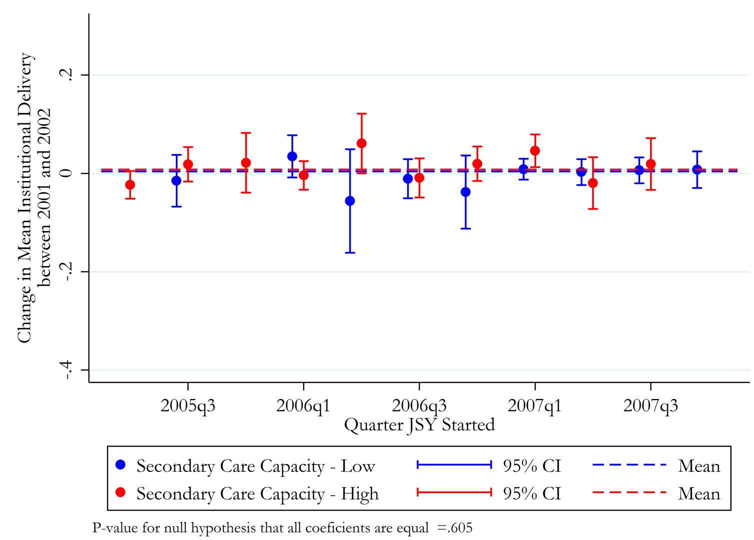
(a) All districts



(b) By Primary Care Capacity



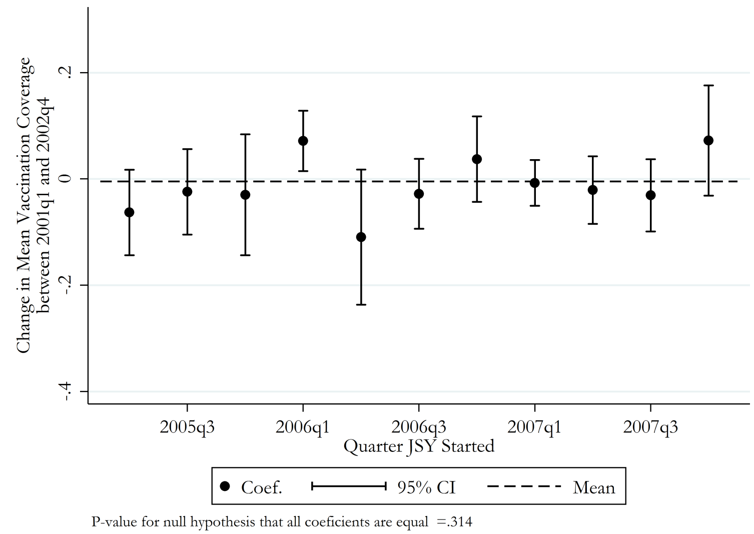
(c) By Secondary Care Capacity



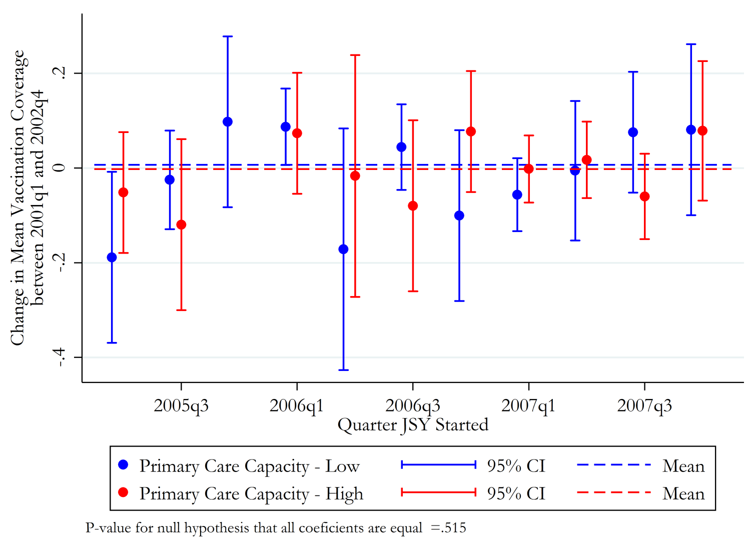
Notes: Figures plot regression coefficients and 95% confidence intervals from district level regressions of 'short differences' in the proportion of births occurring in health facilities between 2001 and 2002 (estimated from DLHS-II) on (a) the quarter when JSY started and (b,c) the quarter when JSY started fully interacted with indicators of whether pre-existing capacity in the primary and secondary healthcare system was above or below the median. DLHS-II asks only (for all districts) about place of birth of children born in 2001 and early 2002. This dictates the short differences used here. In addition, it only asks year of birth for stillbirths which prevents us from assessing short differences between non-consecutive quarters. Regressions omit the constant term. The dashed lines show average coefficients across all quarters. p-values for testing the null hypothesis that all coefficients are equal printed below.

Figure A.5: Examination of parallel pre-trends in Vaccination Coverage infant mortality by JSY rollout

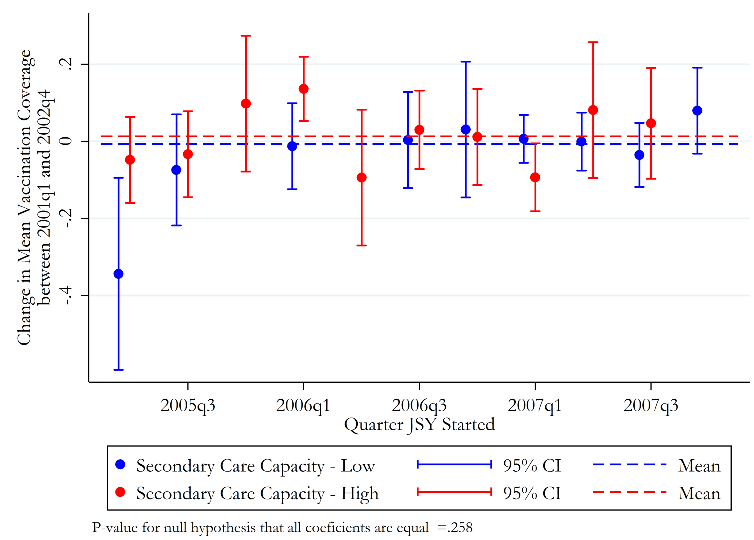
(a) All districts



(b) By Primary Care Capacity



(c) By Secondary Care Capacity



Notes: Figures plot regression coefficients and 95% confidence intervals from district level regressions of 'short differences' in the proportion of children being fully up to date with vaccinations between 2001 and 2002 (estimated from DLHS-II) on (a) the quarter when JSY started and (b,c) the quarter when JSY started fully interacted with indicators of whether pre-existing capacity in the primary and secondary healthcare system was above or below the median. DLHS-IIasks only (for all districts) about vaccinations of children born in 2001 and early 2002. This dictates the short differences used here and the somewhat mechanical 'decrease' in vaccination rates which does not account for the difference in ages at point surveyed. Regressions omit the constant term. The dashed lines show average coefficients across all quarters. p-values for testing the null hypothesis that all coefficients are equal printed below.

A.2 Treatment Effect Decomposition

Under the specification described by equation 4.1, β identifies the average effect (at a particular event time) of JSY on the risk of perinatal mortality across births. This is, of course, a policy relevant treatment effect. However, it is useful to decompose the average effect of JSY on perinatal mortality into (i) a component driven by the effect of JSY moving some births into healthcare facilities that would otherwise have happened at home and (ii) a component driven by JSY changing the riskiness of facility births vis-a-vis home births.

To this end, we adopt a potential outcomes framework where:[23]

1. Whether or not birth i occurs in a facility ($I_i = 1$) or at home ($I_i = 0$) depends on whether or not JSY is active:

$$I_i(JSY)$$

2. Whether or not birth i ends in perinatal mortality ($Y_i = 1$) depends both on (i) whether or not the birth occurred in an facility and (ii) whether or not JSY was active:

$$Y_i(I_i, JSY)$$

   Thus, for each birth there are four potential outcomes for perinatal mortality: $Y_i(0,0)$, $Y_i(0,1)$, $Y_i(1,0)$ and $Y_i(1,1)$.

Using the notation of (Imbens and Wooldridge 2009) we can characterise four distinct groups of births that occur with the following proportions:

1. **Never-takers**. These are births where $I_i(0) = I_i(1) = 0$, i.e. births that would occur at home regardless of whether JSY was active or not. Let π_n be the proportion of never-takers in the population.

[23] We drop dependence on birth order, district and quarter of birth for convenience but note that this is accounted for in all analysis.

2. **Always-takers**. These are births where $I_i(0) = I_i(1) = 1$, i.e. births that would occur in a healthcare facility regardless of whether JSY was active or not. Let π_a be the proportion of always-takers in the population.

3. **Compliers**. These are births where $I_i(0) = 0$, $I_i(1) = 1$, i.e. births that would occur at home if JSY were not active but would occur in a facility if it were. Let π_c be the proportion of compliers in the population.

4. **Defiers**. These are births where $I_i(0) = 1$, $I_i(1) = 0$, i.e. births that would occur at a facility if JSY were not active but would occur at home if it were. Let π_d be the proportion of defiers in the population.

We can therefore decompose the average treatment effect into the weighted average of the average treatment effects for each of these subgroups:

$$
\begin{aligned}
\mathrm{E}(Y_i(JSY=1) - Y_i(JSY=0)) = &\pi_c \,\mathrm{E}(Y_i(1,1) - Y_i(0,0)|\, i \in complier) \\
&+ \pi_a \,\mathrm{E}(Y_i(1,1) - Y_i(1,0)|\, i \in always-taker) \\
&+ \pi_n \,\mathrm{E}(Y_i(0,1) - Y_i(0,0)|\, i \in never-taker) \\
&+ \pi_d \,\mathrm{E}(Y_i(0,1) - Y_i(1,0)|\, i \in defier)
\end{aligned}
\tag{A.2.1}
$$

We now make two further assumptions:

Assumption 1: JSY does not change the home-birth potential outcome, i.e. $Y_i(0,1) = Y_i(0,0)$

Assumption 2 There are no defiers, $\pi_d = 0$.[24]

[24]Note that this may not be reasonable if either JSY reduce the quality of institutional delivery in a way that was observable and caused some parents who would otherwise have given birth in a facility to choose to give birth at home once JSY was implemented.

Given assumptions 1 and 2:

$$\begin{aligned} \mathrm{E}(Y_i(JSY=1) - Y_i(JSY=0)) =& \pi_c \, \mathrm{E}(Y_i(1,1) - Y_i(0,0) | i \in \mathit{complier}) \\ &+ \pi_a \, \mathrm{E}(Y_i(1,1) - Y_i(1,0) | \, i \in always - taker) \end{aligned} \tag{A.2.2}$$

Which further simplifies to equation (4.5):

$$\begin{aligned} &\mathrm{E}(Y_i(JSY=1) - Y_i(JSY=0)) \\ =& \pi_c \, \mathrm{E}(Y_i(1,0) - Y_i(0,0) | \, i \in \mathit{complier}) \\ & \pi_c \, \mathrm{E}(Y_i(1,1) - Y_i(1,0) | \, i \in \mathit{complier}) \\ & + \pi_a \, \mathrm{E}(Y_i(1,1) - Y_i(1,0) | \, i \in always - taker) \\ =& \pi_c \, [\text{ACE of institutional delivery (in absence of JSY) on mortality risk for } \textit{complier} \text{ births}] \\ & + \pi_c \, [\text{ACE of JSY on mortality risk associated with institutional delivery for } \textit{complier} \text{ births}] \\ & + \pi_a \, [\text{ACE of JSY on mortality risk associated with institutional delivery for } \textit{always-taker} \text{ births}] \end{aligned} \tag{A.2.3}$$

A.3 Differential Mortality and Vaccination Results

Our object of interest is the average causal effect of JSY on vaccination rates. Adopting a potential outcomes framework, let $V_i(JSY = 0)$ denotes the proportion of child i's vaccinations that are complete in the state of the world where JSY is not in operation at the time of her birth and $V_i(JSY = 1)$ be the proportion complete in the state of the world where JSY is in operation. Our object of interest is thus:

$$E(V_i(1) - V_i(0)) \tag{A.3.1}$$

A problem is that we only observe $V_i(.)$ if the child survived until the time of the survey. Let $S_i(JSY)$ take the value 1 if birth i survived until the time of survey and 0 otherwise. These missing data for births that did not survive imply that Equation (4.1) does not render an unbiased estimate of (A.3.1) if those births that survived have systematically different vaccination outcomes than those births that didn't would have had. Moreover, Equation (4.1) does not render an unbiased estimate of the average impact of JSY even for those births that survive if JSY changed which births survive and survivors have systematically different vaccination outcomes from non-survivors.

To assess the possibility that our finding that JSY reduced the vaccination rate is driven by JSY altering how many and which births survived until the time of survey we conduct a simple bounding exercise. Given our hypothesis that JSY especially in low capacity areas, impacted the riskiness of births already occurring in health facilities we allow for non-monotonic attrition as a result of JSY, i.e. that there might be both births that may have survived under JSY but who would not have survived otherwise ($Pr(S_i(0) = 0, S_i(1) = 1) \neq 0$) and births that may have not survived under JSY but would have survived otherwise $Pr(S_i(0) = 1, S_i(1) = 0) \neq 0$. Being unwilling to assume monotonicity renders Lee bounds invalid (Lee 2002; Lee 2009). We thus put no assumptions on how JSY affected which births survived. This is very conservative since clearly many births that resulted in perinatal mortality would have done so with or without JSY. And likewise, one would have thought that most deaths that occurred after 1 day have age would have been unaffected by JSY.

We decompose (A.3.1) into an observable and unobservable component:

$$E(V_i(1) - V_i(0)) = E(V_i((1)|S_i((1) = 1))Pr(S_i(1) = 1) - E(V_i((0)|S_i((0) = 1))Pr(S_i(0) = 1) \tag{A.3.2}$$

$$+ E(V_i((1)|S_i((1) = 0))Pr(S_i(1) = 0) - E(V_i((0)|S_i((0) = 1))Pr(S_i(0) = 0)$$

Given we know which births survived we can bound $E(V_i(1)-V_i(0))$ for different assumed boundary values of $E(V_i((1)|S_i((1) = 0))$ and $E(V_i((0)|S_i((0) = 1))$.

Since our estimated effect of JSY on vaccination rates is negative we focus on the upper bound and ask how extreme would potential outcomes on the non-surviving births have to be to nullify this negative effect, i.e. to turn the upper bound positive. In practice we do this by replacing $V_i(.)$ for all births that didn't survive by the assumed boundary value of $E(V_i((1)|S_i((1) = 0))$ or $E(V_i((0)|S_i((0) = 1))$.

Table A.15 shows our estimated upper bounds under different boundary assumptions for $E(V_i((1)|S_i((1) = 0))$ and $E(V_i((0)|S_i((0) = 1))$. It shows that for differential selection to be driving the negative point estimates we obtain it would have be very extreme. For example, fixing the expected vaccination rate for births that didn't survive until the time of survey in post-JSY district-date-of-birth cells to 0.8 implies that the vaccination rate in pre-JSY cells must be as low as 0.2 in order to turn the upper bound positive. We consider there to be few reasons why the vaccination rate would differ considerably between non-surviving births pre- and post- JSY (i.e. that it would deviate from the diagonal of Table A.15) and certainly no reason to expect a difference as great as what would be required to overturn a negative upper bound. We thus consider our results to be robust to plausible values of differential survival.

Table A.15: Upper bounds for Effect of JSY on Vaccination Rates

$E(V_i((1)\|Y_i((1)=1))$	$E(V_i((0)\|Y_i((0)=1))$ 0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
0	**[.,-0.0189]**	**[.,-0.0219]**	**[.,-0.0249]**	**[.,-0.0278]**	**[.,-0.0308]**	**[.,-0.0338]**	**[.,-0.0368]**	**[.,-0.0398]**	**[.,-0.0428]**	**[.,-0.0457]**	**[.,-0.0487]**
0.1	**[.,-0.0155]**	**[.,-0.0185]**	**[.,-0.0215]**	**[.,-0.0245]**	**[.,-0.0275]**	**[.,-0.0304]**	**[.,-0.0334]**	**[.,-0.0364]**	**[.,-0.0394]**	**[.,-0.0424]**	**[.,-0.0454]**
0.2	**[.,-0.0121]**	**[.,-0.0151]**	**[.,-0.0181]**	**[.,-0.0211]**	**[.,-0.0241]**	**[.-,0.0271]**	**[.-,0.0300]**	**[.-,0.0330]**	**[.-,0.0360]**	**[.-,0.0390]**	**[.-,0.0420]**
0.3	**[.-,0.0088]**	**[.-,0.0117]**	**[.-,0.0147]**	**[.-,0.0177]**	**[.-,0.0207]**	**[.-,0.0237]**	**[.-,0.0267]**	**[.-,0.0296]**	**[.-,0.0326]**	**[.-,0.0356]**	**[.-,0.0386]**
0.4	**[.-,0.0054]**	**[.-,0.0084]**	**[.-,0.0114]**	**[.-,0.0143]**	**[.-,0.0173]**	**[.-,0.0203]**	**[.-,0.0233]**	**[.-,0.0263]**	**[.-,0.0293]**	**[.-,0.0322]**	**[.-,0.0352]**
0.5	**[.-,0.0020]**	**[.-,0.0050]**	**[.-,0.0080]**	**[.-,0.0110]**	**[.-,0.0139]**	**[.-,0.0169]**	**[.-,0.0199]**	**[.-,0.0229]**	**[.-,0.0259]**	**[.-,0.0289]**	**[.-,0.0318]**
0.6	[.,0.0014]	**[.-,0.0016]**	**[.-,0.0046]**	**[.-,0.0076]**	**[.-,0.0106]**	**[.-,0.0135]**	**[.-,0.0165]**	**[.-,0.0195]**	**[.-,0.0225]**	**[.-,0.0255]**	**[.-,0.0285]**
0.7	[.,0.0047]	[.,0.0018]	**[.-,0.0012]**	**[.-,0.0042]**	**[.-,0.0072]**	**[.-,0.0102]**	**[.-,0.0132]**	**[.-,0.0161]**	**[.-,0.0191]**	**[.-,0.0221]**	**[.-,0.0251]**
0.8	[.,0.0081]	[.,0.0051]	[.,0.0022]	**[.-,0.0008]**	**[.-,0.0038]**	**[.-,0.0068]**	**[.-,0.0098]**	**[.-,0.0128]**	**[.-,0.0157]**	**[.-,0.0187]**	**[.-,0.0217]**
0.9	[.,0.0115]	[.,0.0085]	[.,0.0055]	[.,0.0026]	**[.-,0.0004]**	**[.-,0.0034]**	**[.-,0.0064]**	**[.-,0.0094]**	**[.-,0.0124]**	**[.-,0.0153]**	**[.-,0.0183]**
1	[.,0.0149]	[.,0.0119]	[.,0.0089]	[.,0.0059]	[.,0.0029]	**[.-,0.0000]**	**[.-,0.0030]**	**[.-,0.0060]**	**[.-,0.0090]**	**[.-,0.0120]**	**[.-,0.0150]**

Notes: Cells in bold indicate a negative point estimate on the upper bound.