

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

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Abstract

If overcrowding harms healthcare quality, the impacts of encouraging more people to use services are not obvious. Impacts will depend on whether marginal entrants benefit and whether they benefit enough to offset the congestion externalities imposed on infra-marginal users. We develop a general-equilibrium model that formalizes these ideas. We examine them empirically by studying JSY, a program in India that paid women to give birth in medical facilities. We find evidence that JSY increased perinatal mortality in areas with low health-system capacity, particularly harmed more-complex births, reduced the quality of facilities' postnatal care, and generated harmful spillovers onto other services.

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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. The additional demand may lead to a congestion externality if, by causing fixed resources to be spread more thinly, it results in the quality of care falling for everyone, including those who would have used the care without any subsidy. Moreover, when healthcare quality is poor, the marginal group who take up care due to the incentive may not benefit. Finally, to manage an increase in demand for the incentivized care, providers may substitute effort and resources away from other types of care, which could risk a wider deterioration in quality.

This paper examines 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 as a set of simple medical procedures can mitigate the vast majority of mortality risks

¹For example, many conditional cash transfer programs condition payments on the take-up of healthcare (Lagarde, Haines, and Palmer 2009).

²See, for example, Das et al. (2016), Das et al. (2008) and Mohanan et al. (2015).

³The JSY payment is Rs. 1400 in the states we focus on (see Section 3). The average daily wage for casual labor (across rural areas) in 2004/5 was Rs. 48.89 (NSS, 61st round).

⁴Authors’ calculations using District Level Household and Facility Survey-3 and National Family Health Survey-4.

associated with childbirth for both mother and infant (Lawn et al. 2005). The pervasive poor quality and low capacity of much of India’s government health system might explain why bringing births into medical facilities had no overall effect on health. At less than 1% of GDP, India’s public spending on health is a third (relative to national income) 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 (Chaudhury et al. 2006).⁵

This study explores the effects of incentivizing the demand for healthcare in this highly supply-constrained system. We begin by creating a flexible general-equilibrium model of birth outcomes and families’ decisions about whether to deliver at home or in a facility. Crucially, we allow for births to be heterogeneous in their complexity and in how much births gain (in expectation) from taking place in a facility. We allow births to sort into facilities endogenously, whether partially, or fully or not at all on the basis of these gains. Key to our model is a congestion, or overcrowding, externality that causes the expected riskiness of all births in medical facilities, and especially the most-complex facility births, to increase when the overall use of facilities rises relative to their capacity.

In our model, the introduction of a subsidy has two effects. First, it results in private benefits (or harms) to the marginal births that take place in a different location as a result of the subsidy. Second, it results in social costs to the births that would have already occurred in facilities, the inframarginal facility births, which now become riskier because of increased congestion. The degree to which births select into facility delivery based on their private gains plays an important role in shaping both effects. For example, in the extreme case of perfect selection on gains (a classic Roy model), the marginal births will be harmed by being incentivized into facilities as these births were making a privately optimal choice to deliver at home before the subsidy. Moreover, in this case the inframarginal facility births that will be exposed to the additional congestion are the most-complex births, which are precisely the births that are most harmed by congestion. In this extreme case, then, a subsidy unambiguously worsens health outcomes.

⁵Source: <http://apps.who.int/nha/database>.

On the other hand, our model highlights that there are circumstances where a subsidy could improve health outcomes. The more complex the marginal births are that are brought into facilities due to the subsidy, the more they will benefit from the move. At the same time, the fewer complex births that occur in facilities to start with, the smaller the aggregate size of the congestion externality. Weak initial sorting on gains but a marginal utility of receiving the subsidy that is increasing in birth complexity could give rise to such conditions.⁶ While it is theoretically ambiguous, and ultimately an empirical question, how the impact of the subsidy varies with respect to pre-existing capacity, we show that there are several channels through which higher pre-existing capacity increases the chance that a subsidy will be useful.

We examine the impacts of JSY empirically, focusing on two dimensions of heterogeneity that our model suggests will be key: pre-existing system capacity and birth complexity. We use geographic disparities in the pre-existing capacity of district health systems – disparities caused by the central government’s 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 capacity (specifically the numbers of doctors, nurses, and beds relative to the size of the population served) affected its impacts.

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 government-run 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. Here caseload increased by a factor of 2.5, from 1.92 deliveries per facility per day to 4.80. We show evidence that while there was some degree of sorting on gains – more-complex births were more likely to occur in facilities than less-complex births both before and after JSY – JSY

⁶For instance, poorer women may have higher average birth complexity if they have less access to prenatal care and might also have a higher marginal utility of consumption.

did not disproportionately draw in complex births. More- and less-complex births were equally likely to be marginal to the subsidy, suggesting that JSY was not particularly effective at targeting the deliveries that would have privately gained the most from moving to a facility.

We show that in these districts with below-median capacity in the secondary health-care 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 before JSY. While JSY caused the same increase in the institutional delivery rate in areas with above-median pre-existing capacity, it had no impact on perinatal mortality, neither positive nor negative, in these areas. We further show that this increase in perinatal mortality risk was entirely concentrated on complex births. This pattern of heterogeneity can, in our model, only be rationalized by the presence of a congestion externality. Moreover, we find that JSY reduced the probability that infants received any check-up between two and ten days after a facility birth, which could indicate that facilities reacted to congestion by discharging women earlier, or by reducing check-ups for babies still in inpatient care.

Our empirical analysis goes further by examining whether the above responses are short-lived and whether the effects of the subsidy spill over into other areas of care. We present more tentative evidence suggesting that harmful effects of JSY in low-capacity areas may have persisted up to five to ten years after the start of JSY: over this period, low-capacity areas with higher compliance with JSY had higher mortality than low-capacity areas with lower compliance. Finally, we also find that stimulating demand for institutional delivery had adverse spillover effects on the proportion of children who were up to date with all vaccinations.

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 without reducing the quality of services should be a first-order consideration when deciding whether to adopt demand-side incentives. These considerations are likely to be particularly crucial in determining whether to incentivize the take-up of invasive, time-consuming and potentially risky procedures such as institutional delivery.

Our paper contributes to several literatures. First, it contributes to the study of demand-side incentives in health, which have proved especially popular policies in LMICs (Kremer and Glennerster 2011; Dupas and Miguel 2017). We bring an explicit focus on congestion and offer a flexible general-equilibrium model of the health effects of incentives in the presence of congestion externalities. Demand incentives are generally effective at increasing uptake of healthcare (Lagarde et al. 2009; Giedion and Díaz 2010) and therefore, unless there is spare or rising capacity in the system, will increase congestion. The mixed evidence on the impact of such incentives on health is consistent with the idea that congestion externalities might be key to shaping their effects. 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 (see the review by Lagarde et al. (2009)). However, when demand for more invasive procedures has been targeted with no change to the supply side, studies, including previous studies of the effect of JSY, have generally not found health benefits (Giedion and Díaz 2010; Das and Hammer 2014; Powell-Jackson et al. 2015; Okeke et al. 2020). Conversely, where the supply side has been improved simultaneously, health benefits have often followed (Miller et al. 2013; Gruber et al. 2014; 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 depends directly on quality. Finally, by exploring heterogeneity by case complexity, we provide evidence that congestion externalities, rather than only the private impacts of healthcare on the marginal cases, are important in limiting the effectiveness of demand-inducing policies in low-capacity areas.

Second, this paper adds to the evidence on the importance of healthcare quality. In many health systems in LMICs, including in rural India, inputs such as trained health professionals and equipment are often not effectively translated into evidence-based care (Chaudhury et al. 2006; Das et al. 2008; Das et al. 2016; Das et al. 2018; Mohanan et al. 2015). 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 increased use of healthcare translates into health outcomes.⁷ Interestingly, we find that capacity in secondary-care health facilities is a very important predictor of the impacts of increasing institutional deliveries on health.

Third, our paper contributes to the literature on congestion externalities in health systems. Overcrowding has been the focus of much attention within the medical literature (Hoot and Aronsky 2008), and a growing number of papers have also considered these issues from an economic perspective (Freedman 2016; Hoe 2022; Marks and Choi 2019). We focus on India’s public health system, which, similarly to public health systems in many LMICs, operates with far fewer resources than the systems in the USA or UK where the empirical economic research on congestion externalities has focused to date. We might expect congestion externalities to play a more prominent role in such resource-constrained settings. Differently from much of the empirical work, which has focused on day-to-day fluctuations in demand (Freedman 2016; Hoe 2022; Marks and Choi 2019), we focus on a context where a high level of congestion is a constant feature of the health system and thus we explicitly model how patients endogenously react to congestion in choosing whether or not to seek healthcare.

The final literature we contribute to considers the spillover effects from policies that target one aspect of healthcare onto another aspect, in line with Holmstrom and Milgrom (1991). Previous work has found that when health providers are incentivized in reimbursement contracts to carry out more of a certain procedure, this often comes at the expense of non-incentivized tasks (e.g. Dumont et al. (2008)). Our paper is the first to assess whether incentivizing the *demand* for specific procedures leads to a deterioration in the use or quality of other procedures. 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 prompted by JSY provided no aggregate health

⁷While 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.

benefits but caused a reduction in childhood vaccinations.

This paper proceeds as follows. Section 2 sets up our conceptual framework. Section 3 provides a basic overview of JSY while Section 4 discusses our data, choice of sample and construction of measures. Section 5 presents our methods and results for assessing the impact of JSY and discusses the different mechanisms. Section 6 concludes.

2 Conceptual Framework

We begin by creating a theoretical model to clarify the different mechanisms through which subsidizing facility delivery might affect birth outcomes. We develop a general equilibrium model of both health and facility choice that allows births of heterogeneous complexities to select into facility delivery endogenously. Crucially, the model allows for congestion externalities whereby an increase in the overall use of facilities increases the risk associated with facility delivery for all births.

Given the model’s various mechanisms, it does not provide an unambiguous prediction of whether or not subsidizing demand will improve health outcomes, although it nests a classic Roy model that does give unambiguous predictions. Instead, our goal is to characterize the features of the underlying environment that will shape a subsidy’s impact.

2.1 Set-up

Determinants of health. Births are indexed by i and may result in either a good health outcome ($H_i = 1$) or a bad health outcome ($H_i = 0$). We allow births to be heterogeneous in their ex-ante risk, in how much they gain or lose from facility delivery, and in the degree to which they suffer from congestion. We summarize this heterogeneity by allowing births to differ along one underlying dimension: their “complexity”, denoted by η_i . Without loss of generality, we assume that η_i is uniformly distributed across the interval $[0, 1]$, with 0 being the least-complex birth and 1 being the most complex.

Women may give birth either at home ($F_i = 0$) or in a health facility ($F_i = 1$). We let the ex-ante probability of a good health outcome for home birth i be denoted $\pi^h(\eta_i)$

while the ex-ante probability of a good health outcome from a facility birth is $\pi^f(F/X, \eta_i)$, where X is capacity, $F \equiv \int_i F_i di$ is overall usage, and F/X is congestion. We make the following assumptions over how complexity affects the private costs/benefits from facility birth:

A1. More-complex births are always more risky than less-complex births that occur in the same location: $\frac{d\pi^h(\eta_i)}{d\eta_i} < 0$ and $\frac{d\pi^f(F/X, \eta_i)}{d\eta_i} < 0$, $\forall F/X$.

A2. More-complex births have more to gain (or less to lose) from facility delivery: $\frac{\partial \pi^f(F/X, \eta_i)}{\partial \eta_i} - \frac{d\pi^h(\eta_i)}{d\eta_i} > 0$, $\forall F/X$.

Our model nests a model with no congestion externality. In that case, we have assumptions A1 and A2 and a “no externality” condition (i.e. $\frac{d\pi^f(F/X, \eta_i)}{d(F/X)} = 0 \quad \forall \eta_i$). If a congestion externality is present, then we further assume the following:

E1. Increased congestion increases the risk of facility births: $\frac{d\pi^f(F/X, \eta_i)}{d(F/X)} < 0$, $\forall \eta_i$.

E2. More-complex births are at least as harmed by congestion as less-complex births: $\frac{d^2 \pi^f(F/X, \eta_i)}{d(F/X) d\eta_i} \leq 0$.

E3. The harmful effects of congestion on the health of facility births are increasing in current congestion: $\frac{d^2 \pi^f(F/X, \eta_i)}{d(F/X)^2} < 0$.

Preferences. In the absence of any subsidy, let utility over place of birth be driven by a consideration for health and a consideration for non-health costs and benefits, with the weight given to health being $\lambda \in [0, 1]$. Then let utility be derived from a subsidy s at a marginal rate of $\theta(\eta_i)$, with $\theta(\eta_i) > 0$, $\forall \eta_i$, which we consider as the marginal utility of consumption and which is allowed to depend on the complexity of the birth. The possibility of this dependence can capture, for example, the idea that more-complex births might be disproportionately from poorer families, who may derive higher utility from the subsidy than richer families. Overall, then, we denote utility as:

$$u(H_i, F_i, \eta_i, \nu_i) = \lambda H_i + (1 - \lambda) F_i \nu_i + F_i \theta(\eta_i) s \quad (2.1)$$

where ν_i is an idiosyncratic preference for facility delivery. Given this preference is likely to be formed of many different factors (e.g. tastes, family tastes, social norms, or distance to a facility) the central limit theorem suggests ν_i will be well approximated by a normal distribution. We assume this distribution is independent from birth complexity: $\nu_i|\eta_i \sim N(\bar{\nu}, \sigma_\nu^2)$. Thus, expected utility is:

$$\tilde{U}(F_i, \eta_i, \nu_i) = \lambda[F_i\pi^f(F/X, \eta_i) + (1 - F_i)\pi^h(\eta_i)] + (1 - \lambda)F_i\nu_i + F_i\theta(\eta_i)s \quad (2.2)$$

Although not formally modelled, we note that a lack of responsiveness to ex-ante risk (i.e. a low λ) could be driven by uncertainty over birth complexity rather than families not valuing health outcomes per se.

2.2 Social Planner's Problem

We first consider the allocation of births to facilities that a social planner trying to maximize overall health would choose.⁸ We assume that the social planner can perfectly observe each birth's complexity, and thus each birth's ex-ante risk conditional on place of delivery. Conditional on allocating a fraction F of births to facilities, the social planner will always assign the fraction F with the highest complexity. In other words, the social planner will perfectly sort births based on their ex-ante gains from facility delivery. The red line in Figure 1 plots the private benefits gained by the marginal births as the planner allocates more and more births to facilities. This curve slopes downwards for two reasons: (1) as the proportion of births occurring in health facilities increases, the complexity of the marginal birth falls and with it the idiosyncratic gain for the marginal birth falls; (2) as the total number of births in facilities increases, crowding increases, facility quality decreases, and the gain for the marginal births decreases.

[FIGURE 1 AROUND HERE]

⁸ This is equivalent to a social planner maximizing welfare without knowledge of idiosyncratic preferences.

In choosing how many births to allocate to facilities, the planner will trade-off gains to the marginal births with the marginal increase in the congestion externality (the “social marginal cost”, or the dashed line in Figure 1), which is experienced by all births already taking place in facilities. The social planner chooses F to equate the social marginal cost from moving an additional birth to the facility with the private marginal benefit to the birth that is moved. This social optimum is marked as point A on Figure 1.

2.3 Decentralized Location Choice and Sorting

We next explore the decentralized equilibrium where families choose where to deliver based on their own preferences and ex-ante risk, without considering any externalities. We assume that families have rational expectations; that their beliefs about ex-ante risk associated with home and facility births and how this is impacted by complexity and congestion are correct, and that they are accurately able to predict how the introduction of the subsidy will affect overall facility usage. Given our set-up, the probability that a birth of complexity η_i will occur in a facility given congestion F/X and subsidy s , which we define $\bar{F}(\eta_i, F/X, s)$, is:

$$\begin{aligned}\bar{F}(\eta_i, F/X, s) &= Pr\left(\lambda\pi^f(F/X, \eta_i) + (1 - \lambda)\nu_i + \theta(\eta_i)s > \lambda\pi^h(\eta_i)\right) \\ &= \Phi\left(\frac{\frac{\lambda}{1-\lambda}[\pi^f(F/X, \eta_i) - \pi^h(\eta_i)] + \frac{1}{1-\lambda}\theta(\eta_i)s + \bar{\nu}}{\sigma_\nu^2}\right)\end{aligned}\quad (2.3)$$

In equilibrium, the proportion of births occurring in facilities is the fixed point, F :

$$F = \int_0^1 \Phi\left(\frac{\frac{\lambda}{1-\lambda}[\pi^f(F/X, \eta_i) - \pi^h(\eta_i)] + \frac{1}{1-\lambda}\theta(\eta_i)s + \bar{\nu}}{\sigma_\nu^2}\right) d\eta_i \quad (2.4)$$

In Appendix Section B.2, we show that $\frac{dF}{ds} > 0$, that is, a subsidy will unambiguously increase the proportion of facility births. The degree to which births of complexity η_i are marginal to the subsidy is described by $\frac{d\bar{F}(\eta_i, F/X, s)}{ds}$ (Equation (B.8) in Appendix B).

2.4 Health impacts of the subsidy

Let $\bar{H}(\eta_i, X, s)$ be the proportion of good health outcomes for births of complexity η_i when capacity is X and the subsidy is s :

$$\bar{H}(\eta_i, X, s) = \bar{F}(\eta_i, F/X, s) \left[\pi^f(F/X, \eta_i) - \pi^h(\eta_i) \right] + \pi^h(\eta_i) \quad (2.5)$$

Differentiating with respect to s , we see that the marginal impact of a subsidy on the proportion of good health outcomes for births of complexity η_i is composed of two effects:

$$\frac{d\bar{H}(\eta_i, X, s)}{ds} = \underbrace{\frac{d\bar{F}(\eta_i, F/X, s)}{ds} \left[\pi^f(F/X, \eta_i) - \pi^h(\eta_i) \right]}_{(1) \text{ Private Cost/Benefit to Marginal Birth}(s)} + \underbrace{\bar{F}(\eta_i, F/X, s) \frac{d\pi^f(F/X, \eta_i)}{d(F/X)} \frac{1}{X} \frac{dF}{ds}}_{(2) \text{ Crowding externality on current facility births}} \quad (2.6)$$

Appendix B.1 gives the full expressions for the total differentials.

In words, effect (1) is the expected private health cost or benefit to marginal births of complexity η_i . It is the difference in ex-ante risk between facility and home births for births of complexity η_i at the current levels of crowding (F/X) weighted by the extent to which births of this complexity are marginal to the subsidy. Effect (2) is the congestion externality. It is the reduction in the probability of a good health outcome from facility births of complexity η_i that occurs because of the overall increase in facility births due to the subsidy. This is scaled by the proportion of births of complexity η_i that will be subject to this externality (i.e. the proportion currently taking place in facilities).

To find the overall effect, we average across complexities:

$$H(X, s) = \int_0^1 \bar{H}(\eta_i, X, s) d\eta_i, \quad \frac{dH(X, s)}{ds} = \int_0^1 \frac{d\bar{H}(\eta_i, X, s)}{ds} d\eta_i \quad (2.7)$$

Overall, a positive subsidy will be optimal whenever there is a marginal gain in health from moving from a zero subsidy to a marginally positive subsidy, i.e. whenever $\frac{dH(X, s)}{ds}|_{s=0} > 0$. This will depend on the sign and magnitude of the private marginal benefits accrued, and, if these are positive, then whether they are large enough to offset

the congestion externality imposed on births currently taking place in facilities. We now discuss each effect in turn.

2.4.1 Private Benefits/Costs to the Marginal Births

The sign and size of the marginal private costs or benefits will depend on which births are marginal to the subsidy. The more complex the set of marginal births is, the more the marginal births will gain from being moved into facilities.

In our framework, the complexity of the marginal births depends both on: (1) the weight that families give to ex-ante health risk in the decision about where to deliver, λ , and (2) on how the marginal utility from the subsidy ($\theta(\eta_i)$) varies across the complexity distribution. Figure 2 illustrates how varying both of these factors changes, across the complexity distribution, the prior probability that births will occur in facilities (plot a), the degree to which births are marginal to the subsidy (plot b) and the private marginal benefits/harms from the subsidy. We construct example scenarios using parametric functional forms for $\pi^h(\eta_i)$, $\pi^f(F/X, \eta_i)$ and $\bar{\theta}(\eta_i)$ (see Appendix Section B.3.3 for details). Each example scenario is calibrated to match pre-JSY mortality rates (3.7%), facility delivery rates (20%), and to have a constant aggregate responsiveness of facility usage to the subsidy (plot c).

As shown by the “high sorting” (blue dashed lines) example in Figure 2, a high λ , indicating a high degree of selection on gains, implies that the most-complex births already largely occur in facilities even without the subsidy (plot (a)), which means that they are not marginal to the subsidy (plot (b)). In this scenario, the subsidy will primarily draw in the next most-complex births out of the births currently taking place at home (plot (b)).

As λ approaches 1, the model approaches a pure Roy model with complete selection on gains. In this case, without the subsidy, births select into facilities in the order of their complexity (from the most complex to the least complex) until the marginal private health gain to the last birth is zero (marked by point B on Figure 1). Even without the congestion externality means that too many births occur in facilities relative to the social

optimal (point A on Figure 1). Subsidizing demand in this case unambiguously worsens health. Under perfect selection on gains, the marginal birth to an infinitesimally small subsidy brings in births that are unaffected by whether or not they occur in a facility. A discrete increase in the subsidy (point C on Figure 1) brings in births that are harmed by the fact that they are now taking place in a facility. This is on top of any costs from the overcrowding externality.

[FIGURE 2 AROUND HERE]

If births respond only very weakly to ex-ante health risk in selecting into facilities (i.e. if λ is low), then there is a pool of highly-complex births that currently take place at home and could gain a lot from being moved into facilities. If the marginal utility of consumption $\theta(\eta_i)$ is independent of η_i (as in the red solid line in Figure 2), the subsidy will always draw in the births uniformly from across the complexity distribution. However, if the marginal utility of consumption $\theta(\eta_i)$ is increasing in birth complexity (as demonstrated by the black dashed line in Figure 2) then more-complex births will be more likely to be marginal. Since more-complex births have more to gain from facility delivery, this would result in larger private gains from the subsidy. Such a scenario might arise if complex births are disproportionately from poorer families, who might for example, have poorer access to prenatal care and a higher marginal utility of consumption.

2.4.2 Congestion Externality

[FIGURE 3 AROUND HERE]

In the presence of a congestion externality (i.e. if E1 through E3 are true) then an increase in aggregate facility usage due to the subsidy will decrease the probability that facility births of all complexities result in a good outcome. As shown in Figure 3(c), in our framework it will always be the most-complex births that will be most harmed by increased congestion. This is for two reasons. First, under sorting on gains, more-complex births are more likely to occur in facilities to begin with and therefore to be exposed to the congestion (Figure 3(a)). Second, by assumption E2 more complex facility births

are more harmed by congestion than are less complex facility births (Figure 3(b)). More generally, the more births that occurred in facilities to begin with and the more elastic total facility usage is to the subsidy, the greater the size of the externality.

2.4.3 Impact of Pre-Existing Capacity

When there is no sorting on gains, the initial equilibrium is independent of capacity and higher pre-existing capacity will unambiguously mean a subsidy is more beneficial (or less harmful) because higher capacity: (1) increases the health gain for marginal births; (2) means the identical absolute increase in facility usage translates into a smaller increase in congestion F/X ; and (3) means the marginal increase in congestion will be less harmful because higher-capacity areas are starting from a lower initial level of congestion (Assumption E3). When there is sorting on gains, including in the extreme case of the Roy model ($\lambda = 1$), how capacity affects the impact of a marginal subsidy will be theoretically ambiguous, as we document in Appendix B.3. Thus, this is ultimately an empirical question. Intuitively, the same three factors as listed above go in the direction of a subsidy being more useful, or less harmful, in higher-capacity areas. However, higher-capacity areas will have more births already occurring in facilities, and thus more births will suffer from the increase in congestion.

2.5 Conclusions from the Model

Our model illustrates that the impact of a demand subsidy for facility delivery is theoretically ambiguous, rendering it a key question for empirical research. It highlights that the impact of a subsidy will be composed of two key effects: first, the benefits/costs to the marginal births; and, second, social costs to all facility births due to the congestion externality.

The framework illustrates that how health impacts from the subsidy vary across the distribution of birth complexity is informative about whether or not a congestion externality is at play, or whether impacts can be explained by the aggregation of private gains/losses to the marginal births alone. Conditional on being marginal to the subsidy,

private benefits are likely to be concentrated on more-complex births and any private costs concentrated on less-complex births. Conversely, any social costs due to a congestion externality will always be concentrated on complex births. This insight is key to how we interpret our findings in Section 5.5.

The model shows that a positive subsidy is optimal if the marginal births benefit from being moved into facilities *and* the magnitude of this benefit outweighs the externality cost borne by births already occurring in facilities. This is more likely to be the case if facilities are less crowded (more capacity, less usage) to begin with, and if it is more-complex births (who have more to gain from facility delivery) who are marginal to the subsidy.

3 JSY and Background on Institutional Delivery

JSY was launched in April 2005 with the aim of reducing maternal and infant mortality through increasing rates of institutional delivery (Ministry of Health and Family Welfare Government of India 2005). Health professionals and women have a role in endogenously sorting births into different types of facilities (primary or secondary). We do not observe this process and we focus simply on whether or not the birth occurred in any health facility.

Many life-saving procedures can only be carried out in health facilities or by a trained birth attendant (Lawn et al. 2005) which creates many reasons why facility delivery could improve birth outcomes, especially for more-complex births. However, evidence of poor quality in the form of few health professionals compounded by absenteeism, a lack of physical resources, and the presence of dangerous pathogens could all reduce the potential gains from facility delivery or even make facility delivery more risky than home birth (Chaudhury et al. 2006; Das et al. 2008; Mohanan et al. 2015; Das et al. 2016). We note, though, that under a congestion externality it could be case that all births gain privately from facility delivery yet the aggregate impact of increasing facility delivery on birth outcomes is negative.

We focus on JSY's effects on rural households in states which the scheme designated as "Low Performing States" based on their low prior institutional delivery rates. In rural areas of these states, JSY is universal and cash incentives are more generous than in either "High Performing States" or in urban areas. Specifically, JSY provides a financial incentive of Rs.1400, or USD 32, to all pregnant women who give birth in a government health facility.⁹ JSY also provides an incentive of Rs. 600, or USD 14, to community health workers for every pregnant woman they bring to a facility. JSY did not provide new funding to help facilities expand obstetric services (Ministry of Health and Family Welfare Government of India 2005).

4 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".¹⁰ 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 2001.¹¹

4.1 Perinatal Mortality and Place of Birth

Data on perinatal mortality, defined as stillbirth after 22 weeks of pregnancy or death within seven days of birth, come from the 2007-08 DLHS-3 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

⁹Exchange rate: 44 Rs./USD (April 2005). By contrast, in High Performing States only pregnant women with a Below Poverty Line card are eligible and transfers are lower (Rs. 700). Urban births also receive lower transfers (Rs. 1000).

¹⁰These are Uttar Pradesh, Chhattisgarh, Bihar, Madhya Pradesh, Rajasthan, Assam, Orissa, Jharkhand and Uttarakhand. Jammu and Kashmir was also designated a "Low Performing State" but we estimate that JSY only began in a single district before 2008 and so we drop it from all analysis.

¹¹Calculated from DLHS-2 using sample weights.

(World Health Organization 2006). As our sample, 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 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 is available for each respondent’s most recent birth, and thus effects here should be interpreted as averages for this sub-population.

[TABLE 1 AROUND HERE]

4.2 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-care and secondary-care facilities.¹² We use the facility survey of the DLHS-2 which, in 2003, surveyed government health facilities in 182 of the 256 districts we focus on in this paper. These data cover all secondary-care health facilities and a random sample of primary-care health centers (PHCs). 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. Further details and density plots of these measures are given in Figure A.1.

We use exploratory factor analysis to assess the dimensionality of these six measures and to create summary indices. We first run a single factor analysis on all six measures which estimates that there are two orthogonal factors with eigenvalues greater than one (the Kaiser criterion for retaining a factor) which implies that these measures can be well summarized by two underlying factors: one primarily reflecting secondary capacity and the other primary capacity (factor loadings in columns (1) and (2) of Table A.1). We next run two separate factor analyses for the primary and secondary capacity measures

¹²Secondary-care facilities are hospitals, community health centers, and first referral units.

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

4.3 JSY rollout

We estimate JSY’s rollout from the DLHS-3. 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 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.¹³ There is strong variation in the timing of implementation within and between states (Figure A.2). In robustness analysis, we use an alternative, fractional measure of JSY intensity – the proportion of eligible births that received the payment (see Figure A.3).

As we hope to use the rollout of JSY to identify causal effects, we now examine how the rollout relates to longer-run trends in our outcomes of interest. A correlation 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. We use the DLHS-2 to calculate district-level changes in rates of institutional delivery, seven-day infant mortality, and vaccinations between 1990 and 2001.¹⁴ We then run

¹³The 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.

¹⁴The birth roster in the DLHS-2 does not include stillbirths, so we check for parallel pre-trends only for seven-day mortality. We use “short” differences for vaccination rates (between 2001Q1 and 2002Q4) as DLHS-2 only contains vaccination information

district-level regressions of JSY’s start date on these changes interacted with the prior capacity of the district (Table A.2). Columns (1), (4), and (7) show that the start date of JSY is uncorrelated with long-run changes in these variables, confirming the finding of Powell-Jackson, Mazumdar, and Mills (2015) that the rollout appears uncorrelated with prior trends. The other columns of Table A.2 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. Figures A.4, A.5, and A.6 in Appendix A provide a more detailed analysis and find no evidence that districts where JSY rolled out at different points were on different trends before the program.

5 JSY’s Impact on Birth Outcomes

5.1 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. We exploit the rollout of JSY across districts between its formal launch in April 2005 and the end of 2007. 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:

$$Y_{ibdt} = \alpha + \sum_{k=-9}^9 \beta_k \mathbf{1}\{K_{ibdt} = k\} + \theta_b + \theta_d + \theta_t + \nu_{ibdt}, \quad (5.1)$$

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 for recent births.

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 et al. 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 $H_0 : \beta_{-8} = \dots \beta_{-2} = 0$ – but not for differences in the linear component of pretrends (Borusyak and Jaravel 2017). This test complements our earlier analysis, in Section 4.3, 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. $E[\nu_{ibdt} | \mathbf{1}\{K_{ibdt} = k\}, \theta_b, \theta_d, \theta_t, \forall k = \{-8, \dots -2, 0, \dots 9\}] = 0$. 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. Under this assumption, and the assumption of no systematic heterogeneity in treatment effects across cohorts (Sun and Abraham 2021), β_k is the average causal effect of JSY k periods after it began.¹⁵

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

$$Y_{ibdt} = \alpha + \sum_{k=-9}^9 \beta_k \mathbf{1}\{K_{ibdt} = k\} + \sum_{k=-9}^9 \gamma_k C_d \mathbf{1}\{K_{ibdt} = k\} + \theta_b + \theta_d + \theta_t + \nu_{ibdt} \quad (5.2)$$

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 $E[\nu_{ibdt} | \mathbf{1}\{K_{ibdt} = k\}, C_d \mathbf{1}\{K_{ibdt} = k\}, \theta_b, \theta_d, \theta_t, \forall k = \{-8, \dots -2, 0, \dots 9\}] = 0$. This rules out that the rollout within districts with the same pre-existing capacity level

¹⁵Table A.14 in Appendix A formally tests for evidence of cohort heterogeneity and finds no evidence of it.

was related to birth-specific risks once conditioning on 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 do not reject the null of no differential non-linear pre-trends, we next place more structure on our analysis to increase precision while maintaining the ability to pick up treatment effects that vary over time. Thus, using the identical sample, we estimate a model that allows the dynamic treatment effect associated with JSY to comprise both a level shift and a trend break:

$$Y_{ibdt} = \alpha + \beta_{shift}JSY_{dt} + \beta_{break}JSY_{dt} \times K_{ibdt} + \theta_b + \theta_d + \theta_t + \nu_{ibdt} \quad (5.3)$$

where JSY_{dt} is an indicator for whether JSY had begun in district d and quarter t , i.e. $JSY_{dt} = \mathbf{1}\{K_{ibdt} \geq 0\}$. 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 (5.1) and (5.2) – 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:

$$\hat{\beta}^{average} = \sum_{k=0}^9 w_k \hat{\beta}_k, \quad \widehat{se}(\hat{\beta}^{average}) = \sum_{k=0}^9 w_k \widehat{se}(\hat{\beta}_k), \quad w_k = \frac{\sum_i \mathbf{1}\{K_{ibdt} = k\}}{\sum_{k'=0}^9 \sum_i \mathbf{1}\{K_{ibdt} = k'\}} \quad (5.4)$$

When treatment effects vary with time, this approach is preferable to a two-way fixed effects regression, 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.

5.2 Impacts on Institutional Delivery

[FIGURE 4 AROUND HERE]

Our event studies 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 4(a)). After two years of operation, the analysis suggests that JSY had increased the probability that a birth took place in a medical facility by around 20 percentage points. Dynamic effects look similar across areas with different pre-existing capacities and we cannot reject that effects prior to JSY’s rollout are zero for all levels of pre-existing capacity (Figure A.7).

Next, we estimate the average of these dynamic effects, weighted according to the event-time distribution of our sample (equation (5.4)). Overall, JSY increased the 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 2, Panel A, column (1)) and 7.62 percentage points across districts with capacity data available (column (2)). These effect sizes are in line with those found by Powell-Jackson, Mazumdar, and Mills (2015). The increase appears similar in districts with more and with less prior capacity (columns (3)-(5)).

As we see in Table A.3 in Appendix A, 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 2 AROUND HERE]

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 A.3) translates into an increase in the average number of births per day occurring in each government-run secondary-care facility, or in a government-run primary-care facility under the supervision of that secondary facility, from 1.73 before 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 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).¹⁶

5.3 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 A.8(a)) and when averaged over event time (Table 2, Panel B, 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. On the one hand, in the former, low-capacity districts, Figure 4(b) shows that JSY increased the risk of perinatal mortality, with effects growing somewhat in magnitude over time. The average impact across event times (Table 2, Panel B, 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 compared to the rate of perinatal mortality of 3.70% in the 15 months before JSY's launch.

¹⁶Taking India's 2005 crude birth rate of 24.2 per thousand people (data.worldbank.org) we estimate the average number of births per day in each district using population figures from the 2001 census. We estimate the average number taking place each day in government health facilities both before JSY's rollout (using the pre-JSY observed rate in the district) and after (using this baseline rate plus 0.0944). We divide these figures by the number of secondary-care facilities in the district.

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 (Table 2, Panel B, columns (4) and (5)). Neither is the difference in effects between districts with high and low primary-care capacity.

5.4 Robustness

In Appendix A, we explore the robustness of our results. We show results using a static two-way-fixed-effects 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.4) are nearly identical to the weighted average of the dynamic effects, which is unsurprising as the dynamic effects do not vary substantially with time (Figure 4). For institutional delivery, the static specification produces smaller, but still highly statistically significant, estimates (Table A.5), which is expected given, as shown in Figure 4, the dynamic effects increase with time (Borusyak and Jaravel 2017). We further show that results are robust to using a probit model (Tables A.6 and A.7) and to using a fractional indicator of JSY’s rollout (Table A.8 and A.9), to using continuous measures of pre-existing capacity (Tables A.10 and A.11) and to allowing for differential time trends by pre-existing capacity (Tables A.12 and A.13). In Table A.14, we show that we find no evidence of heterogeneity in the impact of JSY on perinatal mortality across districts that adopted JSY earlier and later.

Given that health system capacity was not randomly assigned, heterogeneity by capacity could, theoretically, be capturing heterogeneity across distinct but correlated characteristics of districts (see Table A.15). We mostly rely on our conceptual framework to motivate why system capacity is a natural dimension over which heterogeneity would arise. However, we also use LASSO penalized regression to analyze which district characteristics predict heterogeneity in the impact of JSY on perinatal mortality. We allow for heterogeneity to be predicted by district-level measures of: poverty, men’s education, women’s education, distance from different health facilities, and our two measures of system capacity. Figure A.9 shows that at all levels of penalization, the standardized coefficients on both measures of capacity are greater than all alternative predictors.

Moreover, LASSO sets coefficients on all other predictors to zero well before setting either of the capacity coefficients to zero. This reassures us that the heterogeneity we have recovered is not simply standing in for heterogeneity across other dimensions.

5.5 Mechanisms

We have shown that JSY increased the perinatal mortality risk in areas with low pre-existing capacity in the secondary-care system. Our theoretical model demonstrates that two mechanisms could have led to this. Even in the absence of any congestion externality, JSY could harm health if the marginal births moved by the subsidy were riskier when taking place in a facility rather than at home. As discussed in Section 3, if facilities are poor quality, this is not implausible. However, our model also suggests that a second mechanism: that the overall increase in facility delivery rates increased congestion in facilities, leading to a deterioration in the quality of medical care for all facility births, including those that would have taken place in facilities even in the absence of the subsidy.

In this section, we explore the mechanisms at play. We begin by looking at how the impacts of JSY differed by birth complexity as an attempt to shed light on the role of a congestion externality in driving the negative effects of JSY. To this end, we create a proxy for birth complexity by using variables containing information that would have been known to families at the time they were choosing where to deliver: complications experienced during pregnancy, the number of previous pregnancies, whether the woman had previously had a miscarriage, whether she had previously had a stillbirth, and whether she had previously given birth to a baby who subsequently died. We use these variables, and their interactions, to predict perinatal mortality in the full sample for which this information is available (the sample of last births). To do so, we used penalized LASSO regression to avoid overfitting. We then predict a risk index using the chosen predictors. See Table A.17 in Appendix A for details. We divide births into those with a risk index above and below the median.

[TABLE 3 AROUND HERE]

In column (1) of Table 3, we estimate the impact of JSY on institutional delivery using the identical methods to those we employed earlier but now interacting secondary health system capacity with our proxy for birth complexity in addition to JSY's rollout. The first important thing to notice here is that even in the absence of JSY, in both low-capacity (line e) and high-capacity areas (line f), more-complex births were more likely to occur in facilities than less-complex births suggesting that births select into health facilities at least partially on this basis of their expected complexity. While this suggests that, prior to JSY, births sorted into facilities somewhat based on gains, lines (a)-(d) of column 1 show that JSY drew in more-complex and less-complex births to the same degree and this was true in both low- and high-capacity areas.¹⁷ We argued in Section 2 that for JSY to stand the best chance of being effective at improving health outcomes, it would have to disproportionately induce the most-complex births into health facilities. We see here that this does not seem to have been the case.

Next we turn to how JSY's impacts on perinatal mortality differed by births' complexity in column (2). In rows (a) and (b) we see that practically all the increase in perinatal mortality in low-capacity areas was driven by more-complex births. We estimate that the perinatal mortality risk of these complex births in low-capacity areas increased by 1.59 percentage points due to JSY, while less-complex births saw no change. The difference between the two is highly statistically significant. Interestingly, we even see tentative evidence that in higher-capacity areas too, more-complex births may have suffered due to JSY, although to a lesser extent than in low-capacity areas. The fact that the harms of JSY appear to be concentrated on more-complex births despite JSY having moved more-complex and less-complex births into facilities at the same rate suggests that a congestion externality is key to explaining JSY's perverse effects.

¹⁷In itself, this result is not informative on the degree of selection on gains and/or the degree to which the marginal utility of consumption is increasing in birth complexity. As we can see from Figure 2, the fact that the subsidy has the same average impact on usage above and below the median could be the result of different combinations of selection on gains and marginal utility of consumption.

To see this, first imagine the special case of our model with no congestion externality. In this case, all of the aggregate harms due to the subsidy are made up of private harms to the marginal births. In our model, conditional on moving the same proportion of less-complex and more-complex births into facilities (which we see empirically) the more-complex births would privately gain more or be harmed less. Therefore, the fact that harms appear concentrated on complex births is inconsistent with the version of our model without a congestion externality.

However, our model predicts that under sorting on gains (which we see empirically) the overall cost of the externality will be disproportionately borne by complex births. This is the case for two reasons. First, a disproportionate number of complex births will already be occurring in facilities and thus will be subject to the externality. Second, we anticipate (as set out in Assumption E2) that congestion will harm more-complex facility births the most. Thus, the fact that we find clear evidence that the harms associated with JSY are concentrated on complex births is evidence that a congestion externality is crucial to understanding our results.

Besides this indirect evidence on the importance of congestion externalities, the results in columns (3) and (4) provide more direct evidence on congestion. Here we look at whether respondents reported that their baby received a check-up after their facility birth. Note that we condition on births occurring in facilities here as it would be surprising if moving births into facilities did not result in some increase in the proportion reporting a check from a health professional;¹⁸ Instead, we want to focus on the quality of care provided by facilities. In column (3), we look at whether or not respondents reported that their baby received a check-up within the first 24 hours. Overall, we do not see evidence that JSY changed the likelihood of this, which, given that even a very cursory check-up from a health worker would be counted here, is perhaps not surprising. In column (4) we look at whether babies received a check-up between days 2 and 10. We take this as an indicator of how long women remain in facilities after birth, and the intensity of the

¹⁸Table A.16 in Appendix A shows that we do indeed see the overall rate of postnatal care increasing with JSY, although this increase is concentrated in high-capacity areas.

continued care they receive (both in facilities and in the community). Here we find that in low-capacity areas (but not in high-capacity areas) JSY reduced the probability of such check-ups by around 7 percentage points (lines a and b). We interpret this as evidence that in low-capacity areas, facilities reacted to congestion by either discharging women and babies earlier or by providing less continued care. Furthermore, the fact that this reduction was equal for more-complex (line b) and less-complex births (line a) suggests that facilities did not prioritize maintaining more-intensive care for more-complex births in reacting to this congestion.

5.6 Spillovers onto 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 of the same age should have received.¹⁹ Given that polio vaccinations are largely administered by a parallel system, the “Pulse Polio Initiative”, we focus on the six non-polio childhood vaccinations that are delivered through the public health system.

We find that, averaged across event time, JSY reduced 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. Interestingly, the negative effect of JSY on vaccination rates is smaller in vaccines given closer to birth than in those given later. This is consistent with JSY reallocating resources and reducing vaccination rates but this is offset for vaccines given at an early age because JSY also led to an increase in institutional deliveries, which could have increased parents’ attachment to healthcare providers right after birth.

[TABLE 4 AROUND HERE]

Reductions in vaccination rates do not vary with pre-existing capacity (Figure A.10,

¹⁹These data are available for each respondent’s two most recent surviving children.

Table A.18).²⁰ In Appendix A we show these findings are robust to using a static specification (Table A.19), to using a probit model (A.20), and to using a fractional indicator of JSY intensity (A.21). In Appendix C, we argue that these results are not driven by differential selection caused by JSY’s impacts on mortality.

5.7 Tentative evidence on medium-run effects

We have provided evidence that in the short run JSY caused an increase in perinatal mortality in areas with low pre-existing rates of capacity in the secondary-care system. A crucial question is whether this was a short term effect, in which case the impacts could have been due to transition difficulties, or whether JSY’s negative impacts persisted. Here, we briefly attempt to establish whether the available evidence points towards persistence. To do this, we draw on the birth recode of the fourth National Family Health Survey (2014-15). The NFHS-4 records detailed information, including JSY uptake and place of delivery, of all births since 2010 in addition to mortality data for a longer history of births.

In the short term, we used the staggered roll-out of JSY across districts to estimate its effects. However, by 2010 JSY had been operational for upwards of four years in most districts, making this approach less plausible. Instead, we explore how variation in JSY compliance between districts correlates with variation in both institutional delivery rates and perinatal mortality rates over the medium run. Specifically, we create an indicator for whether or not 90% or more of births that should have been eligible for a JSY payment (i.e. births that occurred in a government facility) between 2010 and 2015 reported receiving one. We use the identically constructed measures of pre-JSY health system

²⁰One 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 A.3). 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.

capacity.

Beginning with rates of institutional delivery in Table 5, we find that, after controlling for quarter-of-birth fixed effects, districts where compliance was greater than 90% had institutional delivery rates of 4.5 percentage points greater than in districts with lower compliance (column 1). Note that because we have no historical data from this dataset on institutional delivery, we cannot control for district fixed effects.

We then proceed to analyze the medium-run effects on perinatal mortality. Column (2) shows that districts with 90% or higher JSY compliance had perinatal mortality rates that were 0.71 percentage points higher than districts with lower compliance (controlling for time trends). Columns (3)-(5) show that, consistent with our short-term results, this result is driven by low-capacity areas, although whether the difference is statistically significant depends on the precise specification. Note that these results are subject to some important limitations. In columns (3) and (4) where we only use births from 2010 onwards, the sample size is much smaller than in Table 3 and we cannot include district fixed effects. In column (5), we append the data with births between 2000 and 2005, which enables us to include district-level fixed effects, although this assumes that the unobserved district-level components remain constant over that long period, which is a strong assumption.

[TABLE 5 AROUND HERE]

While the extent to which different districts complied with JSY over the medium run may not be exogenous for many reasons, these associations are certainly consistent with JSY continuing to have perverse effects on perinatal mortality up to 10 years after it was first introduced. The associations are perhaps most convincing at suggesting that it is unlikely that the short-term harmful impacts of JSY in low-capacity areas turned beneficial over the medium run. In many ways, this seems unsurprising given that since JSY's introduction in 2005, India's public spending on healthcare has remained unchanged at less than 1% of GDP, far less than other rapidly growing economies. Low and steady levels of public expenditure since JSY's introduction perhaps gave little scope for a rapid improvement in the capacity of the supply side over this period.

6 Conclusions

Conditional cash transfer programs are frequently used to increase the uptake of health services, but evidence on their impact on health is mixed (Lagarde et al. 2009). In this paper, we bring to the fore the role of congestion externalities in explaining the detrimental effects of JSY on perinatal mortality in areas of India that have a low-capacity healthcare system. The overall impact of JSY on health is composed of both its effect on inframarginal facility births (those that would have taken place in a facility regardless of JSY) and its effect on marginal births (those births induced to take place in the facility because of JSY). Under a congestion externality, the effect on the inframarginal births will always be detrimental due to increased congestion. Hence, for JSY to improve outcomes, any positive effect on marginal births must outweigh the congestion externality.

The theoretical model highlights interesting interactions between the size of the congestion externality and what drives selection into institutional delivery. Under full selection on gains, the inframarginal facility births are the riskiest and, consequently, they are the most harmed by the additional congestion caused by JSY. Moreover, under full selection on gains, the births that are marginal to JSY are harmed from switching from home to facility delivery. Hence, in this case, JSY will have detrimental effects on health. On the contrary, if the initial selection into health facilities is unrelated to health gains, then there could be a large pool of potentially-marginal births that could gain a lot from facility delivery. Furthermore, if more complex births are more responsive to the subsidy, this would give JSY a better shot at attracting the births that would particularly gain more from facility delivery.

Unfortunately, our empirical analysis reveals that JSY was not successful at attracting disproportionately complex births; more- and less-complex births were similarly attracted. Moreover, we find evidence that in low-capacity districts JSY generated additional and harmful congestion. In these districts, JSY decreased the likelihood that babies received a postnatal check-up after the first day, which suggests that they were discharged sooner or simply that check-ups were overlooked. We show that the detrimental effects of JSY were concentrated on complex births, a result which in our model can only be explained

by the presence of a congestion externality. Overall, JSY caused perinatal mortality to increase in low-capacity districts and more tentative evidence suggests that these harmful effects may have persisted for up to 10 years.

Our general equilibrium framework points to alternative approaches on how to use public funds to improve health outcomes when congestion externalities are a concern. First, policies that help identify complex cases and direct those cases toward health facilities could be particularly useful. Our framework demonstrates that, for a given degree of capacity and usage, increasing the complexity of the cases that select into formal healthcare will improve overall health. While there are often important barriers to patients discerning the usefulness of a given healthcare intervention and this is a fundamental barrier to individuals seeking out the optimal amount of care (Arrow 1963), good-quality prenatal care could help direct more complex births towards facilities.

Second, our framework highlights the potential of policies that effectively increase the capacity of healthcare systems and the quality of care they provide, including both policies that increase the resources available and those that ensure those resources are used efficiently (Dupas and Miguel 2017; Kremer and Glennerster 2011; Björkman and Svensson 2009). Our framework suggests that such efforts are likely to improve outcomes for existing users of healthcare and to attract more individuals to take up care. Also, our empirical results highlight the stakes of such efforts to improve quality, especially as efforts intensify to ensure universal access to healthcare. We found that in areas with few of the most basic healthcare inputs – beds, nurses, and doctors – increased use of healthcare harmed overall health.

References

- Arrow, Kenneth J (1963). Uncertainty and the Welfare Economics of Medical Care. *American Economic Review* 53(5), 941–973.
- Bertrand, Marianne, Esther Duflo, and Sendhil Mullainathan (2004). How Much Should We Trust Difference-in-Differences Estimates? *Quarterly Journal of Eco-*

nomics 119(1), 249–275.

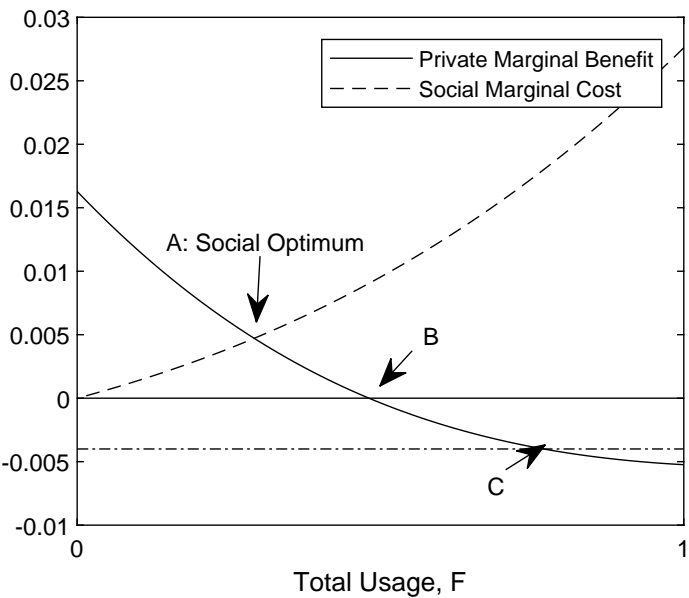
- Björkman, Martina and Jakob Svensson (2009). Power to the People: Evidence from a Randomized Field Experiment on Community-Based Monitoring in Uganda. *Quarterly Journal of Economics* 124(2), 735–769.
- Borusyak, Kirill and Xavier Jaravel (2017). Revisiting Event Study Designs.
- Cesur, Resul, Pınar Mine Güneş, Erdal Tekin, and Aydogan Ulker (2017). The value of socialized medicine: The impact of universal primary healthcare provision on mortality rates in Turkey. *Journal of Public Economics* 150, 75–93.
- Chaudhury, Nazmul, Jeffrey Hammer, Michael Kremer, Karthik Muralidharan, and F Halsey Rogers (2006). Missing in Action: Teacher and Health Worker Absence in Developing Countries. *Journal of Economic Perspectives* 20(1), 91–116.
- Das, Jishnu and Jeffrey Hammer (2014). Are Institutional Births Institutionalizing Deaths? *World Bank Future Development Blog*, 1–8.
- Das, Jishnu, Jeffrey Hammer, and Kenneth Leonard (2008). The Quality of Medical Advice in Low-Income Countries. *Journal of Economic Perspectives* 22(2), 93–114.
- Das, Jishnu, Alaka Holla, Aakash Mohpal, and Karthik Muralidharan (2016). Quality and Accountability in Health Care Delivery: Audit-Study Evidence from Primary Care in India. *American Economic Review* 106(12), 3765–3799.
- Das, Jishnu, Liana Woskie, Ruma Rajbhandari, Kamran Abbasi, and Ashish Jha (2018). Rethinking assumptions about delivery of healthcare: Implications for universal health coverage. *BMJ* 361, k1716.
- Dumont, Etienne, Bernard Fortin, Nicolas Jacquemet, and Bruce Shearer (2008). Physicians’ multitasking and incentives: Empirical evidence from a natural experiment. *Journal of Health Economics* 27(6), 1436–1450.
- Dupas, P and E Miguel (2017). Impacts and Determinants of Health Levels in Low-Income Countries. In Abhijit V Banerjee and Esther Duflo (Eds.), *Handbook of Economic Field Experiments*, Volume 2, pp. 3–93. Amsterdam: Elsevier Ltd.

- Freedman, Seth (2016). Capacity and utilization in health care: The effect of empty beds on neonatal intensive care admission. *American Economic Journal: Economic Policy* 8(2), 154–185.
- Giedion, Ursula and Beatriz Yadira Díaz (2010). A review of the evidence. In Maria-Luisa Escobar, Charles C Griffin, and R Paul Shaw (Eds.), *The Impact of Health Insurance in Low- and Middle-Income Countries*, pp. 155–177. Washington, DC: Brookings Institution Press.
- Gruber, Jonathan, Nathaniel Hendren, and Robert M Townsend (2014). The Great Equalizer: Health Care Access and Infant Mortality in Thailand. *American Economic Journal: Applied Economics* 6(1), 91–107.
- Hoe, Thomas P (2022). Does Hospital Crowding Matter? Evidence from Trauma and Orthopedics in England. *American Economic Journal: Economic Policy* 14(2), 231–262.
- Holmstrom, B and P Milgrom (1991). Multitask Principal-Agent Analyses: Incentive Contracts, Asset Ownership, and Job Design. *Journal of Law, Economics, and Organization* 7(special), 24–52.
- Hoot, Nathan R and Dominik Aronsky (2008). Systematic Review of Emergency Department Crowding: Causes, Effects, and Solutions. *Annals of Emergency Medicine* 52(2), 126—136.e1.
- Kremer, Michael and Rachel Glennerster (2011). Improving Health in Developing Countries. In *Handbook of Health Economics*, Volume 2, pp. 201–315. Amsterdam: Elsevier B.V.
- Kumar, A K.Shiva, Lincoln C Chen, Mita Choudhury, Shibam Ganju, Vijay Mahajan, Amarjeet Sinha, and Abhijit Sen (2011). Financing health care for all: Challenges and opportunities. *The Lancet* 377(9766), 668–679.
- Lagarde, M, A Haines, and N Palmer (2009). The impact of conditional cash transfers on health outcomes and use of health services in low and middle income countries (Review). *Cochrane Database of Systematic Reviews* (4).

- Lawn, Joy E, Simon Cousens, and Jelka Zupan (2005). 4 million neonatal deaths: When? Where? Why? *The Lancet* 365(9462), 891–900.
- Marks, Mindy and Moonkyung Kate Choi (2019). Baby Boomlets and Baby Health: Hospital Crowdedness, Hospital Spending, and Infant Health. *American Journal of Health Economics* 5(3), 376–406.
- Miller, Grant, Diana Pinto, and Marcos Vera-Hernández (2013). Risk protection, service use, and health outcomes under Colombia’s health insurance program for the poor. *American Economic Journal: Applied Economics* 5(4), 61–91.
- Ministry of Health and Family Welfare Government of India (2005). Janani Suraksha Yojana Guidelines for Implementation.
- Mohan, Manoj, Marcos Vera-Hernández, Veena Das, Soledad Giardili, Jeremy D Goldhaber-Fiebert, Tracy L Rabin, Sunil S Raj, Jeremy I Schwartz, and Aparna Seth (2015). The know-do gap in quality of health care for childhood diarrhea and pneumonia in rural india. *JAMA Pediatrics* 169(4), 349–357.
- Okeke, Edward N., Zachary Wagner, and Isa S. Abubakar (2020). Maternal Cash Transfers Led To Increases In Facility Deliveries And Improved Quality Of Delivery Care In Nigeria. *Health Affairs* 39(6), 1051–1059.
- Powell-Jackson, Timothy, Sumit Mazumdar, and Anne Mills (2015). Financial incentives in health: New evidence from India’s Janani Suraksha Yojana. *Journal of Health Economics* 43, 154–169.
- Rao, Mohan, Krishna D Rao, Ak Shiva Kumar, Mirai Chatterjee, and Thiagarajan Sundararaman (2011). Human resources for health in India. *The Lancet* 377(9765), 587–598.
- Sun, Liyang and Sarah Abraham (2021). Estimating dynamic treatment effects in event studies with heterogeneous treatment effects. *Journal of Econometrics* 225(2), 175–199.
- World Health Organization (2006). Neonatal and perinatal mortality: Country, Regional and Global Estimates. Technical report.

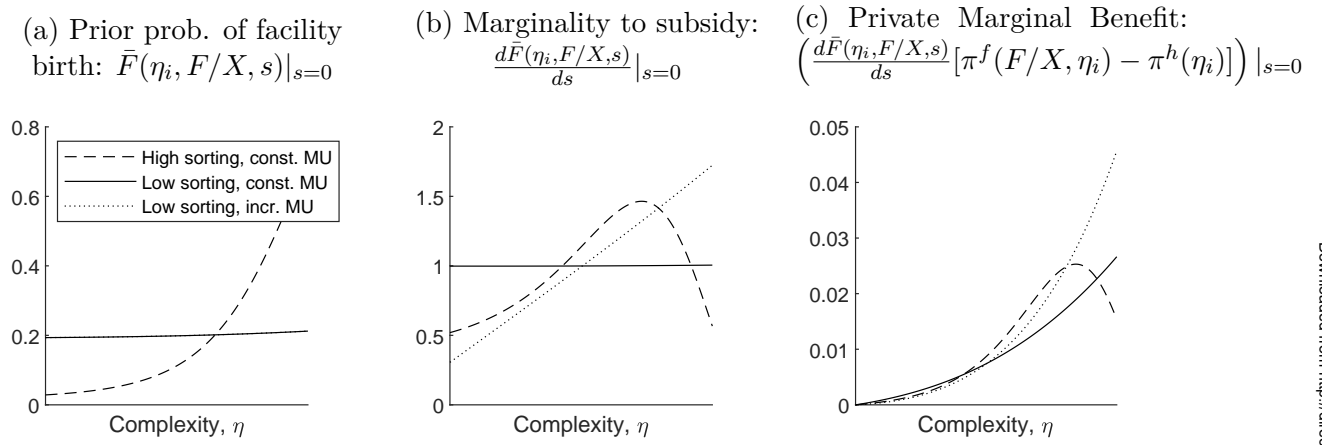
7 Figures

Figure 1: Social Planner’s Problem



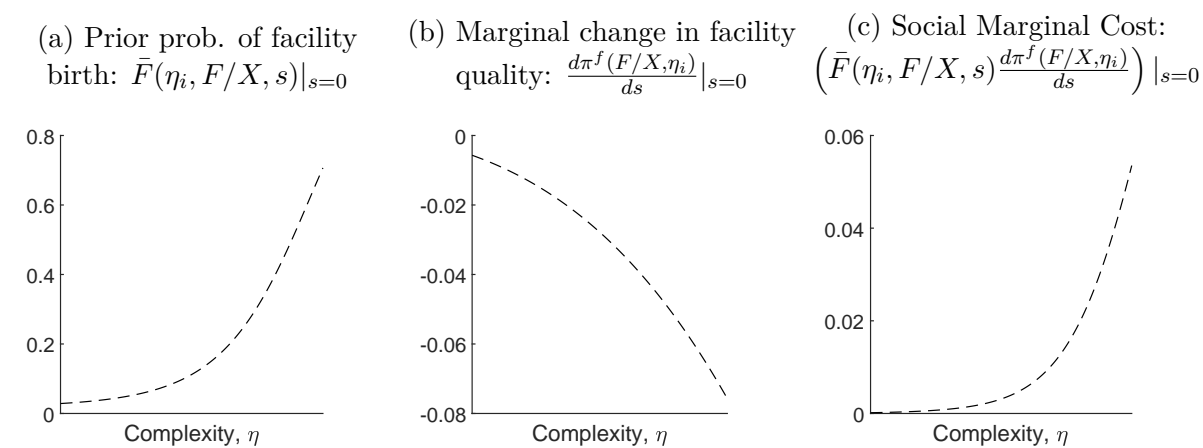
Notes: Figure plots the private benefit to the marginal birth and the social marginal cost to all births already in facilities as more births enter under the condition that births enter in the order of their complexity, from most complex first to least complex last. Points B and C are discussed in Section 2.4.1.

Figure 2: The same increase in institutional delivery rates due to a subsidy will translate into higher health gains if there is little initial sorting on health gains but the marginal utility (MU) of consumption is increasing in birth complexity.



Notes: Figure plots, by complexity: (a) the prior probability of facility birth (equation (2.3)); (b) marginality to the subsidy (equation (B.8)); and (c) the private marginal benefit from the subsidy (equation (2.6)). Details of the parametric functional forms used for $\pi^h(\eta_i)$, $\pi^f(F/X, \eta_i)$ and $\bar{\theta}(\eta_i)$, parameter choices and calibration are in Appendix B.3.3. In the “high sorting” scenarios, $\lambda = 0.9$ while in the “low sorting” scenarios, $\lambda = 0.2$. In the “const. MU” scenarios $d\bar{\theta}(\eta_i)/d\eta_i = 0$ while in the “incr. MU” scenario $d\bar{\theta}(\eta_i)/d\eta_i > 0$.

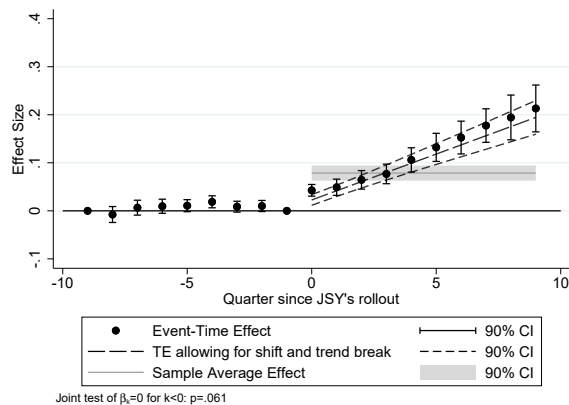
Figure 3: Under sorting on gains, the costs of the congestion externality will be concentrated on complex births.



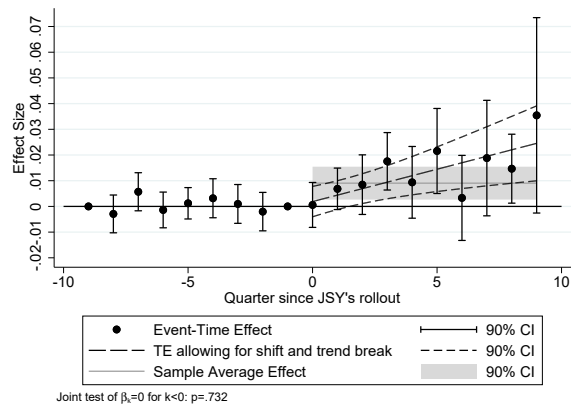
Notes: Figure plots, by complexity : (a) the prior probability of facility birth (equation (2.3)); (b) the marginal reduction in facility quality due to the subsidy (equation (B.4)); and (c) the social marginal cost from the externality (equation (2.6)). Details of the parametric functional forms used for $\pi^h(\eta_i)$ $\pi^f(F/X, \eta_i)$ and $\bar{\theta}(\eta_i)$, parameter choices and calibration are in Appendix B.3.3.

Figure 4: Dynamic Effects of JSY

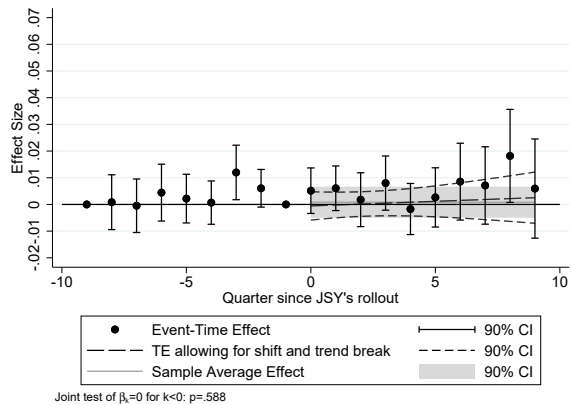
(a) Effects on institutional delivery



(b) Effects on perinatal mortality
(low secondary-care capacity)



(c) Effects on perinatal mortality
(high secondary-care capacity)



Notes: Figures plot dynamic effects of JSY on: (a) institutional delivery (all districts), (b) perinatal mortality in low secondary-care capacity districts, and (c) perinatal mortality in high secondary-care capacity districts. Each figure plots: (1) the event-time effects (equations 5.1 and 5.2). We plot coefficients β_k (in graphs a and b), $k = -9, \dots, 9$ and $\beta_k + \gamma_k$ (in graph c); (2) dynamic effects allowing for a level shift and a trend break as estimated from equation (5.3); (3) average effects of JSY as defined in equation (5.4).

8 Tables

Table 1: Sample Descriptives

	Mean	Standard Deviation	N
<i>Birth Outcomes</i>			
Perinatal Mortality	0.0398	0.195	104057
Stillbirth	0.0153	0.123	104057
Died within 7 days Live birth	0.0248	0.156	102461
<i>Place of Birth</i>			
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
<i>Mother Characteristics</i>			
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
<i>Household Characteristics</i>			
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

Table 2: Effect of JSY on Institutional Delivery and Perinatal Mortality by Pre-Existing Capacity

<i>Panel A: Institutional Delivery</i>					
	(1)	(2)	(3)	(4)	(5)
JSY	0.0786*** (0.0095)	0.0762*** (0.0114)	0.0769*** (0.0170)	0.0830*** (0.0127)	0.0748*** (0.0181)
JSY × High secondary cap.			0.0018 (0.0170)		0.0183 (0.0208)
JSY × High primary cap.				-0.0143 (0.0143)	0.0152 (0.0239)
JSY × High sec. × High prim.					-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
<i>Panel B: Perinatal Mortality</i>					
	(1)	(2)	(3)	(4)	(5)
JSY	0.0015 (0.0027)	0.0032 (0.0033)	0.0090** (0.0039)	0.0048 (0.0038)	0.0111** (0.0044)
JSY × High secondary cap.			-0.0082** (0.0035)		-0.0117** (0.0052)
JSY × High primary cap.				-0.0043 (0.0034)	-0.0040 (0.0041)
JSY × High sec. × High prim.					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 (clustered by district) in parentheses. Effects are weighted (weights proportional to sample size, defined in (5.4)) averages of dynamic effects (estimated using specifications (5.1) and (5.2)). All estimates control for quarter-of-birth, birth-order, and district fixed effects. The 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 equalling 1 if district has above-median secondary- (primary-) care capacity, as defined in Section 4.2.

Table 3: Impacts on Institutional Delivery, Perinatal Mortality, and Post-Birth Check-Ups by Birth Complexity

	Institutional Delivery (1)	Perinatal Mortality (2)	Checkup day 1 Facility (2)	Checkup days 2-10 Facility (3)
(a) JSY \times Low sec. \times Low risk	0.0782*** (0.0178)	0.0041 (0.0045)	-0.0042 (0.0250)	-0.0666*** (0.0243)
(b) JSY \times Low sec. \times High risk	0.0755*** (0.0175)	0.0159*** (0.0053)	-0.0373 (0.0257)	-0.0749*** (0.0260)
<i>Difference (b-a)</i>	-0.0027 (0.0099)	0.0118*** (0.0043)	-0.0331* (0.0175)	-0.0083 (0.0203)
(c) JSY \times High sec. \times Low risk	0.0766*** (0.0132)	0.0004 (0.0035)	0.0231 (0.0234)	-0.0000 (0.0261)
(d) JSY \times High sec. \times High risk	0.0802*** (0.0154)	0.0084* (0.0044)	0.0334 (0.0261)	-0.0329 (0.0262)
<i>Difference (d-c)</i>	0.0036 (0.0135)	0.0079* (0.0041)	0.0102 (0.0228)	-0.0328 (0.0231)
(e) Low sec. \times High risk	0.0526*** (0.0063)	0.0176*** (0.0031)	0.0530*** (0.0184)	0.0444** (0.0173)
(f) High sec. \times High risk	0.0701*** (0.0124)	0.0160*** (0.0038)	0.0192 (0.0218)	0.0621*** (0.0226)
Observations	59,880	59,888	16,498	15,858
Number of districts	182	182	182	182
Mean Prior to 2005Q2	0.2260	0.0370	0.6972	0.4225

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors (clustered by district) in parentheses. Effects are weighted (weights proportional to sample size, defined in equation (5.4))) averages of dynamic effects (estimated using specification (5.2)). All estimates control for quarter-of-birth, birth-order, and district fixed effects. High sec. is an indicator equalling 1 if district has above-median secondary care capacity, as defined in Section 4.2. More-complex (less-complex) births are defined as those with above (below) median values for the LASSO-predicted index of birth complexity (detailed in Table A.17 in Appendix A).

Table 4: 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*** (0.00757)	-0.00818 (0.00741)	-0.0134* (0.00805)	-0.0114 (0.00993)	-0.0311*** (0.0109)	-0.0322*** (0.00909)	-0.0225** (0.00920)
Observations	79298	96284	95886	95175	93894	79298	79298
Age of Administration (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 (clustered by district) in parentheses. Effects are weighted (weights proportional to sample size, defined in equation (5.4)) averages of dynamic effects (estimated using specification (5.1)). All estimates control for quarter-of-birth, birth-order, and district fixed effects. Sample for each regression includes all children who are older than the recommended age of administration for that vaccination (displayed here as “months at admin.”. Sample for the mean coverage rate (column (1)) includes only children older than 9 months who should have received all vaccinations.

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Table 5: Relationship between JSY intensity, Institutional Delivery and Perinatal Mortality after 2010

	(1) Inst. Del.	(2) Mort.	(3) Mort.	(4) Mort.	(5) Mort.
High Intensity	0.0452** (0.0218)	0.00710*** (0.00249)	0.00743* (0.00438)	0.00732** (0.00368)	0.00726* (0.00385)
High sec. cap. × High Intensity			-0.00462 (0.00577)	-0.00907* (0.00533)	-0.00662 (0.00556)
Historical perinatal mort. rate				0.515*** (0.0894)	
Observations	24277	38589	27815	27815	110805
Quarter of Birth FEs	x	x	x	x	x
State FEs				x	
District FEs					x
Sample: Post-2010 births	x	x	x	x	x
Sample: Pre-2005 births					x

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors (clustered by district) in parentheses. High secondary cap. is an indicator equalling 1 if district has above-median secondary-care capacity, as defined in Section 4.2. Pre-2005 sample comprises births from 2000 up until the launch of JSY in 2005, quarter 2. Historical perinatal mortality rates calculated using this pre-2005 sample.