Private Hospital Behavior Under Government Insurance: Evidence from Reimbursement Changes in India

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Abstract

In a major shift away from direct public provision, governments around the world are expanding public insurance programs that contract the private sector to deliver health services at pre-specified reimbursement rates. These rates are a key policy lever to shape provider incentives, but there is little evidence on their effects in lower-income contexts with limited regulatory capacity. Using over 1.6 million insurance claims and 20,000 patient surveys, and exploiting a policy-induced natural experiment, this paper provides evidence on private hospital responses to reimbursement rate changes under government health insurance in India. It shows that: 1) Private hospitals engage in coding manipulation to increase revenues at government expense. Manipulation is highly responsive to changes in the relative reimbursement rates of similar services. 2) Rate increases also induce an increase in service volumes. 3) Hospitals charge patients for care that should be free under program rules. Raising rates reduces these charges significantly, but hospitals capture about half of the increase. Pass-through is driven entirely by less concentrated markets, suggesting that hospitals exploit market power to capture public subsidies. There is no evidence of changes in care quality or patient composition. These findings highlight the critical role of prices and market structure when contracting the private sector for delivery of social services.

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1 Introduction

A hundred million people fall into poverty due to out-of-pocket health spending each year and half of the world's population does not have access to essential health services (WHO 2021). For decades, governments in lower-income countries have focused on direct provision of free or very low-cost health services through public hospitals and clinics. However, widespread quality and leakage problems have been well documented (Di Giorgio et al 2020; Das et al 2016; Das & Hammer 2014; Chaudhury et al 2006) and political economy constraints have made public sector reform difficult (Dhaliwal & Hanna 2017, Banerjee et al 2008). As an alternative, governments are increasingly scaling up public health insurance programs that target low-income households and contract the private sector for service delivery in order to increase access to hospital care while providing financial protection

Outsourcing service delivery to the private sector can leverage market forces and increase efficiency, access, and quality. To the extent that consumers have better information on care quality than the government does, market incentives can induce greater effort and better services despite weak government oversight (Das et al 2016). However, profit-maximizing private agents may have interests that are in tension with social objectives, and monitoring and appropriately incentivizing them comes with its own challenges. In particular, the prices the government sets for health services determine their profitability and may affect provider behavior in ways that affect both government spending and program outcomes.

A large literature examines private hospital behavior in higher-income countries, and shows that how hospitals are compensated has significant implications for service volumes, quality, and health outcomes (Dranove 1987; Ellis & McGuire 1986; Cutler 1995). However, it is unclear to what extent these findings generalize to lower-income contexts like India. In settings like the U.S. Medicare program, prices are based on local hospital costs and are risk-adjusted. Because such detailed, systematic data on hospital costs and patient health are not available in lower-income countries, prices are typically based on crude estimates, are unadjusted for health risk or care quality, and may not correspond well to the costs of care provision. Additionally, because monitoring and enforcement capacity is weak, ensuring that hospitals comply with the prices and don't overcharge the government or patients is difficult. Therefore, how private hospitals behave within insurance, and particularly how they respond to prices, may be very different in countries with weaker robust price-setting, regulatory, and monitoring systems. Understanding these effects is critical to ensuring the efficiency and effectiveness of public spending on insurance, but has been difficult due to data constraints.

This paper provides the first large-scale evidence on how reimbursement rates (prices) affect private hospital behavior and the performance of government health insurance in India. The study context is the BSBY public health insurance program in Rajasthan, India, which entitles 46 million low-income individuals, or more than half the state's population, to free and "cashless" care at public and empaneled private hospitals. Two-thirds of participating hospitals and about 75% of all insurance claims filed in the first 4 years of the program are in the private sector. Like many such programs, in order to contain program costs, BSBY employs a prospective payment system that reimburses hospitals at a pre-specified, fixed rate per service, that covers all tests, medicines, and hospital costs, rather than a fee-for-service system, where hospitals are paid for each procedure performed. Hospitals file claims for services provided and are directly reimbursed at the prespecified rates so that patients pay nothing at the hospital. The program is almost identical in design to insurance programs in other Indian states and the recently launched national PMJAY program that aims to cover the poorest 40% of the Indian population, and is very similar to insurance programs in countries like Indonesia, Mexico, and Ghana.

In December 2017, two years after program launch, the government revised hospital reimbursement rates for different services by varying magnitudes. This creates a clean natural experiment to study how hospitals respond. Using administrative data on 1.6M insurance claims filed in the 6-7 months before and after the reform, linked to 20,000 post-visit patient surveys, this paper studies the effect of changes in reimbursement rates on coding behavior, patient out-of-pocket (OOP) spending, and service volumes.

I first show that private hospitals engage in substantial coding fraud ("upcoding"), where they file claims for higher-reimbursed services than those they actually provide in order to increase their revenues. The composition of claims filed by hospitals changes dramatically within a week of the policy reform: a 1% increase in the reimbursement rate for a service induces a 0.4% increase in its claim volume. Rate changes have no effect on the composition of services at public hospitals, which do not have a financial incentive to increase revenues. The speed, specificity, and magnitude of these changes are suggestive of coding fraud, but survey data provide direct evidence that the accuracy of hospital coding decreases as the reimbursement rate for a service (and the reward to upcoding into it) increases. The evidence reallocate upcoding to services where the relative gains are highest, as has been found in other contexts (Dafny 2005, Jürges & Köberlein 2015).

Reimbursement increases also induce a “real” supply response: for every 1,000 INR increase in reimbursement paid to hospitals, service volumes increase by 5.2%, implying an elasticity of approximately 0.44. This volume increase is not explained by an increase in fake claims for “ghost” patients, nor is there a decrease in service volumes at public hospitals that would suggest that private hospitals are simply drawing patients away from the public sector. Effects are larger among hospitals with higher pre-reform volumes. The number of participating private hospitals also increases, but this may be due to changes in empanelment criteria rather than hospital entry induced by higher reimbursements.[1]

The third outcome I examine is patient out-of-pocket (OOP) charges. Although BSBY entitles beneficiaries to free care, surveys with patients shortly after they have received care under BSBY show that hospitals charge patients for their care against program rules. More than three-quarters of hospitals charge a patient and 41% of patients paid for insured care in the 7 months prior to the reform. OOP charges were INR 2,151 ($35), or a 37% markup over the BSBY reimbursement rate, on average. More than half of all patients did not know what the full cost of their care would be prior to their visit. In sum, patients are incompletely insured and face substantial financial risk when seeking care under insurance.

When the government raises the reimbursement rate for a service, hospitals substantially reduce what they charge patients for it, suggesting that the charges are partly explained by ”balance-billing”, where hospitals compensate for reimbursement rates that are set too low to cover their costs by charging patients the difference. However, for every INR100 paid by the government to hospitals, patient OOP charges decrease by no more than INR55, indicating that hospitals capture approximately half of the reimbursement increase as profits. There is no evidence that

[1] The government loosened empanelment criteria at the time of the reform to allow smaller hospitals to participate in the program.

hospitals improve care quality or accept sicker, costlier patients. Decreases in patient OOP charges are driven entirely by more competitive markets with more participating hospitals, suggesting hospitals with market power face weaker incentives to reduce the prices patients pay and can instead pocket government reimbursements.

Taken together, the results show that, in contexts of weak oversight, profit-motivated private agents systematically flout program rules to increase their revenues at the expense of the government and patients. However, a key insight is that this non-compliance partially compensates for prices that are set too low to meet the participation constraints of agents. Given this, simply increasing monitoring, without appropriate price-setting, may increase hospital compliance but decrease the quantity or quality of service provision by pushing hospitals to skimp or exit. On the other hand, increasing reimbursement rates can encourage hospital participation and increase service volumes, but may waste public resources if hospitals are not monitored or rates are too high. The finding that patient charges only decrease in more competitive markets shows that market structure, a factor rarely taken into account in social policy design in lower income contexts, can meaningfully affect the extent to which public subsidies benefit target recipients. By disciplining agents, competition may partially substitute for monitoring, implying that top-down monitoring may be particularly important in less competitive areas. These insights also apply more broadly to contracting the private sector for delivery of social services in settings with limited institutional capacity for monitoring and price-setting.

This paper contributes important new evidence to the literature on the challenges of designing and implementing health insurance programs in lower-income countries. Most studies have evaluated the impacts of health insurance programs in India and around the world on health care utilization or health and financial outcomes, and found mixed results, or have focused on demand-side barriers to effective implementation (King et al. 2009; Thornton et al. 2010; Miller et al. 2013; Levine et al. 2016; Karan et al 2017; Haushofer et al. 2020; Banerjee et al. 2021). This paper provides evidence on how supply-side factors, such as payment systems and private hospital behavior, affect insurance implementation.

A large theoretical and empirical literature has examined the effects of reimbursement rates on private hospital incentives and behavior in higher income countries, including on coding manipulation (Barros Braun 2017, Fang Gong 2017, Geruso Layton 2015, Jurges Koberlein

2015, Dafny 2005, Silverman and Skinner 2004) and the extent to which increased government payments to private providers are passed through and benefit patients (Duggan et a. 2016, Cabral et al 2018, Carey 2021). This paper contributes to these bodies of research with new evidence from India, a lower income country, where large-scale public health insurance programs are relatively new, health care markets are largely unregulated, and the capacity to monitor hospitals limited. Importantly, it shows that fixed prices that aim to share financial risk with hospitals may function very differently in environments of weak contract enforcement and hospital oversight, because hospitals simply pass the risk on to patients.

This paper also contributes to the literature on challenges to implementing public subsidies in settings with weak state capacity. Limited pass-through of government subsidies has been documented in the context of food distribution schemes (Olken 2006 and Banerjee et al 2018 in Indonesia, Nagavarapu and Sekhri 2016 in India), education (Reinikka and Svensson 2004 in Uganda, Ferraz et al 2016 in Brazil), maternity benefits (Mohanan et al 2014), and health insurance benefits (Gertler and Solon 2002). Other studies find muted or null effects of health insurance on household financial risk, but cannot determine what factors drive this (Thornton et al 2010; Karan et al 2017). This paper shows that provider capture contributes to incomplete pass-through and that combining administrative data with phone surveys with target beneficiaries provides a powerful monitoring tool to improve last-mile service delivery and ensure benefits reach the intended population (Muralidharan et al 2021). The finding that patient charges decrease most in competitive markets is consistent with, and contributes to, the relatively small literature examining the role of competition in the extent to which public subsidies reach target beneficiaries in low-income contexts (Busso Galiani 2019, Banerjee et al 2017).

2 Program Context

2.1 The BSBY Program

In December 2015, the Government of Rajasthan, a state of 70 million in western India, launched the Bhamashah Swasthya Bima Yojana (BSBY), a statewide public health insurance program that entitles low-income households to free secondary and tertiary hospital care at all public and empaneled private hospitals in the state. BSBY's design is very similar to that of other state health insurance programs, as well as the national PMJAY program launched in 2018 that aims to cover the poorest 40% of the Indian population.[2] Households on the state poverty list are automatically eligible and enrolled in the program and need only verify their identity at the hospital to obtain care.[3] Approximately 11 million households and 48 million individuals were eligible and enrolled in 2017. Households are entitled to up to a value of INR30,000 (∼$450) in secondary and INR100,000 (∼$1500) in tertiary care per year.[4] Their care is supposed to be free: they face no co-pay and all costs of a visit for an eligible service, including hospital fees, tests, and medicines are covered.

The program covers a prespecified list of services defined based broadly on diagnosis and procedure, and employs a prospective payment system. Each service has a fixed hospital reimbursement rate that covers all procedures, tests, drugs, regardless of the actual cost of care. Rates are set by a panel of public health officials and, because detailed data on hospital costs are unavailable, are based on rough cost estimates from public hospitals, rates used by other state insurance programs, and consultations with private hospital representatives. Rates are uniform across the state, and unadjusted for local input costs or patient case-mix. The same amount reimbursed to a hospital is deducted from the household's annual balance. Empanelled hospitals can choose whether to accept a patient or provide a service under BSBY. Claims are filed, processed, and reimbursed electronically through a centralized system designed and managed by the government.

The New India Assurance Company (hereafter the Insurer), one of India's largest public health insurers, was selected to be the Insurer through a standard public procurement process. Premiums are paid by the government directly to the Insurer on behalf of all eligible households. The

[2] In late 2019, after the period covered in this study, the program was renamed the Ayushman Bharat Rajasthan Swasthya Bima Yojana (AB-RSBY) in preparation for its merger with the national health insurance program.

[3] Households determined to be eligible for subsidized food benefits under the National Food Security Act (NFSA) are automatically eligible for BSBY. NFSA eligibility is based largely on household "below poverty line" (BPL) status, but also includes other vulnerable groups, such as manual scavengers and widows. To verify their identity and eligibility at the hospital, patients must present their Bhamashah card, a biometrically-linked card issued to all households in Rajasthan that identifies and links all members of the household. The card is issued to the female head of household and is linked to a bank account in her name. It is used for delivery of various public benefits, including old age pensions and subsidized food rations.

[4] Although a spending limit is counterintuitive in the context of insurance, this is a standard feature of public helth insurance programs in India and is designed to limit extreme fraud. The limit is largely not binding and only about 1% of BSBY households reach it.

Insurer is responsible for empanelling hospitals, publicizing the program, and processing hospital claims. As the residual claimant on the unspent premium, the Insurer has an incentive to monitor hospitals and minimize fraudulent claims.[5] It reviews claims and the supporting documents (test results, X-rays etc.) hospitals file as proof of services provided, conducts spot visits to check hospital records, and analyzes claims data to identify suspicious patterns. However, monitoring is unsystematic and designed only to catch egregious fraud, and does not include oversight of care quality and informal patient charges. At the time of the study, government monitoring was very limited, but patients could call a phone hotline with complaints.

2.2 Hospital Reimbursement Reform

In December 2017, the first 2-year phase of BSBY ended and the program was renewed for another two years. The primary change between Phases 1 and 2 was the revision of the list of services and corresponding hospital reimbursement rates covered by the program. The program covered a prespecified list of 1,747 unique services in Phase 1 and this was revised to 1,406 services in Phase 2. Most services remained the same, but some that were considered redundant were eliminated or merged and new codes were added where the classifications were previously too coarse or to cover newly eligible services. Reimbursement rates were revised to reflect changing costs; most rates were increased, but some that were thought to be too high were reduced. As with the Phase 1 rates, due to the lack of systematic cost data, the new rates were also based on rough estimates determined by a panel of public health officials with input from private hospitals. The new rates were shared with hospitals in early December and went into effect on December 13, 2017. Because reimbursements are managed electronically, all claims filed after this date were immediately and automatically reimbursed at the new rates.

The government issued a new RFP for an Insurer, but selected the same Phase 1 Insurer. Premiums increased but were paid by the government to the Insurer and did not affect households or hospitals. Insurer responsibilities and the claim filing system remained the same. The household annual benefit limit was increased to INR 300,000 ($4500) for tertiary care. Hospital empanelment criteria were changed slightly to allow smaller facilities to participate in under-

[5]To discourage the Insurer from suppressing legitimate claims, the BSBY contract requires it to return a substantial share of the unspent premium to the government if total claims value is low, thus limiting how much it stands to gain from discouraging claims.

served areas. Because this change makes it difficult to determine whether any hospital entry observed in Phase 2 is due to the looser empanelment criteria or higher reimbursement rates, the analysis largely focuses on already empanelled hospitals. Additionally, public hospitals were no longer reimbursed for child deliveries under BSBY in Phase 2 on the rationale that these are already funded through other government maternal health programs. Child deliveries are among the services included in the study sample, but results are not sensitive to excluding them.

3 Data and Empirical Strategy

The paper uses a combination of BSBY administrative claims data, obtained through a partnership with the state government, and primary data collected through surveys with patients shortly after they had received care under the program.

3.1 Administrative Claims Data

The BSBY program generates real-time data on every insurance claim filed under the program through its centralized electronic claims processing system. These administrative data include the patient's unique household ID, name, age, sex, phone number, and address; the hospital unique ID, name, and district location; and the service code, service name, and reimbursement rate for services provided. They do not, however, include care details, such as tests and medicines provided, test results, or diagnosis, nor information on the hospital's full price outside insurance for the services provided.

As the list of services changed between Phases 1 and 2 (see Section 2.2), services had to be matched across phases to create a stable panel in order to study the effects of reimbursement rate changes. Because services were assigned entirely new codes in Phase 2, with no numerical identifier linking them to Phase 1 codes, the match was done manually using the text descriptions of services, and focused on the highest-volume service areas. Where a service-code was split or two codes were merged between phases, they were combined into a single code that is stable across phases. Closely related service-codes were grouped into "service-clusters". For example, BSBY has separate service-codes for "basic neonatal care (INR 3000)", "specialized neonatal care (INR 5,500)", and "advanced neonatal care (INR 12,000)", which are grouped into a "neonatal care cluster". The final matched panel includes 93 services within 24 different service-clusters. Although these comprise a relatively small share of the available BSBY service-codes, they account for approximately 70% of all claims filed during the study period. The rest of the paper uses service and service-code interchangeably, and service-cluster or cluster for the higher-level groupings of services.

3.2 Survey Data

Updated BSBY claims data were received from the government every two weeks, and were used to sample hospital visits for follow-up patient surveys. Claims for hospital visits over the previous 2 weeks were stratified by hospital sector (public or private) and service-cluster, before a fixed number from each cluster were randomly selected for survey. The survey sample is largely restricted to claims filed by private hospitals, but also includes a sample of child deliveries at public hospitals in Phase 1. Surveys of child delivery claims started in late June 2017, additional services were added in mid-September 2017, once the revised service and reimbursement list was finalized by the government, and all surveys continued through July 2018.

Surveys were conducted by phone using patient phone numbers included in the administrative data, and were completed within 3 weeks of the claim being filed to reduce recall bias.[6] Surveys collected information on patient residence, demographics, care received, cash paid, perceived quality of care, length of hospital stay, knowledge of the insurance program, hospital utilization and morbidity in the previous year, and socioeconomic status (assets, education, caste, and religion). Surveys of childbirth claims included more details on facility choice, prior risk factors, complications at the hospital, delivery type (vaginal or c-section), care components, and measures of WHO recommended quality.

Table 1 presents summary statistics on the claims and survey data in Panels A and B. Over 1.6 million claims were filed for study services by 1,398 hospitals between June 2017 and July 2018. 65% of the hospitals and 54% of claims were in the private sector. Almost 20,000 patients,

[6] The average time between claim filing and survey completion was 25 days, and decreased from 27 days in Phase 1 to 24 days in Phase 2, as surveying procedures improved. Controls for recall period are included in all analyses using the survey data.

or 70% of those sampled, were successfully surveyed over the same period. Surveys focused primarily on private sector claims, but included about 1,000 surveys for pre-reform claims at public hospitals.

3.3 Descriptive Statistics on Out-of-Pocket Charges

Panel C of Table 1 presents descriptive statistics on care at private hospitals for the pre-reform period from June 2017 to December 2107. Over this time, 651 private hospitals filed about 100 claims per month and the mean reimbursement per claim was INR 9,060 ($135). Although BSBY assures patients of free care at participating hospitals, surveys with patients shortly after they have received care under BSBY reveal that the vast majority of hospitals (88%) charge patients. More than a third of patients faced out-of-pocket (OOP) charges for their visit, and charges were INR 2,151 ($35) on average. To put these numbers in context, patient payments constitute a 37% markup over the reimbursement rate. They are also likely to be a substantial share of household earnings, given that eligibility depends on being below the poverty line, or living on less than about $2 per day. Patients also face substantial uncertainty about how much they will have to pay: 46% did not know what the full cost of care would be prior to their hospital visit and about half had to pay additional amounts after being admitted and received care. Under half of all patients did not know BSBY care should be free at the time of the survey. Surveys confirm that the BSBY population is socioeconomically vulnerable: average completed schooling is under 6 years (65% have no schooling), 31% are members of the lowest caste or tribal groups, and half of them have no form of transport, including a bicycle, in their household.

Taken together, these statistics indicate that patients face substantial financial risk despite insurance coverage. Because the survey sample is patients that received a service for which a BSBY claim was filed and the hospital reimbursed, we can be sure these payments are due to hospitals charging patients against program rules. Studies based on population surveys have found that the expansion of insurance has small or no effects on health expenditures. This could be due to problems at various points in the causal chain between insurance availability and patient financial outlays, including eligibility, enrollment, facility access and choice, procedure coverage, or hospital charging behavior. Most of the literature has focused on the role of enrollment, implementation, and patient awareness (Rathi 2003, Seshadri 2012, Rao 2014, Nandi 2015 review). The data in this paper are unique in isolating the contribution of hospital charging behavior to persistent OOP expenditures despite insurance coverage.

3.4 Empirical Strategy

To evaluate the effect of reimbursement changes on hospital behavior, the paper uses a difference-in-difference (DID) approach, exploiting variation in the reimbursement rate change across services induced by the December 2017 policy reform. The analysis focuses on the period from June 2017 through July 2018 for which both claims and survey data are available, excluding December 2017 because the reform took effect in the middle of the month. The analysis focuses on the panel of hospitals participating in BSBY both before and after the policy reform.

3.4.1 Service-level analysis

The first part of the paper examines effects on claims volume and coding composition across service-codes. The service reimbursement rate change treatment variable is the Phase 2 minus Phase 1 rate for a service-code. Where two or more Phase 1 codes were merged into a single Phase 2 code, the rate change is the mean rate change of the component codes, weighted by their Phase 1 claims volume. In the rare cases where a single Phase 1 code was split into multiple Phase 2 service codes, the rate change is the average rate of the Phase 2 component codes minus the Phase 1 rate. Figure 1 shows that the magnitude of rate changes across the 93 services in the study ranges from an 80% reduction to a more than 200% increase.

The administrative claims data are collapsed to create a hospital-service-month level balanced panel of claim volumes. The DID regression specification is as follows:

$$Y_{sht} = \alpha_0 + \beta_1 RateChange_s * Post_t + \gamma_s + \delta_t + \zeta_h + e_{sht} \tag{1}$$

where Y_{sht} is the outcome for service s in hospital h in month t; service, month, and hospital fixed effects are included; e_{sht} is the error term. Standard errors are conservatively two-way clustered at the hospital and service levels (Cameron & Miller 2015). The outcome is claim volumes in log terms, and as a share of total cluster claims. β_1 is the coefficient of interest and represents the change in the outcome for every unit increase in the reimbursement rate of a service.

3.4.2 Cluster-level analysis

A key concern with this empirical strategy is that hospitals may be upcoding, where they file claims for higher reimbursed codes than those provided, and that this may change in response to reimbursement changes. The paper tests for this in Section 4.1 and finds evidence of substantial changes in upcoding after the reform. This makes the DID effects on service volumes difficult to interpret, because coding changes will be conflated with real volume changes. Because the "true" composition of services provided within each code changes, it also complicates interpretation of effects on patient charges if the cost of providing different services differs.[7] However, because all closely-related services are grouped into the same cluster by design, upcoding occurs within and not across service-clusters. Section 4.2 provides empirical support for this. Therefore, the analysis of service volumes and patient charges is conducted at the service-cluster (hereafter cluster) level.

The cluster-level reimbursement rate change treatment variable is calculated as the mean rate change across services in the cluster, weighted by each service's total Phase 1 volumes. This is effectively creates a cluster-level rate change based on the overall Phase 1 composition of each service cluster, and is what the average change in reimbursement for a cluster would be if the program's Phase 1 composition of services across all hospitals remained unchanged in Phase 2. Because this variable is not hospital-specific and because the service composition of clusters changes in Phase 2, the cluster rate change may not translate directly into a one-for-one change in reimbursement rate. However, this method ensures that the cluster predicted rate change is orthogonal to the coding decisions or service composition of any particular hospital and to pre- and post-reform hospital outcomes. Figure 1 shows that the variation in the cluster rate change is less than that at the service level but still substantial, ranging from a 20% reduction to a 70% increase.

To analyze reimbursement effects on care volumes, the claims data are collapsed to create

[7] For example, if patients that actually got service A were being upcoded into service B and this decreased post-reform, the average cost of all patients coded as receiving B is higher post-reform than pre-reform.

a hospital-cluster-month level balanced panel and the DID regression specification is as follows:

$$Y_{cht} = \alpha_0 + \beta_1 ClusterRateChange_c * Post_t + \gamma_c + \delta_t + \zeta_h e_{cht} \tag{2}$$

where Y_{cht} is the claims volume for cluster c in hospital h in month t; cluster, month, and hospital fixed effects are included; e_{cht} is the error term. Standard errors are two-way clustered at the cluster and hospital levels, and wild-cluster bootstrapped p-values that account for the small number of clusters are also presented (Cameron et al 2008, Cameron & Miller 2015). The key coefficient is β_1, which represents the effect of the cluster rate change on the outcome post-reform.

To examine the effects of reimbursement changes on OOP charges and patient and care characteristics, survey data on patient hospital visits are linked to the claims data for those visits and DID regressions of the same form as equation (2) are run at the visit-level. Survey regressions include survey sampling probability weights and control for survey recall period and surveyor fixed effects.

The identifying assumption in the DID empirical strategy is that clusters that experience rate changes of different magnitudes or no rate change have outcomes on parallel trends pre-reform, and that in the absence of the rate changes they would have remained parallel post-reform. The second assumption is untestable, but pre-reform can be used data to examine the first assumption. Figure 3, Figure 4, and Figure 5 present results for several outcomes from event study specifications, where the treatment is interacted with bimonthly dummies over the pre- and post-reform period instead of a single post-reform dummy, and October-November is the reference group. The pre-reform coefficients are insignificant, indicating there were no differential pre-reform trends across treatment groups in any of the key outcomes. Another concern is that the policy reform may have changed other factors correlated with both the reimbursement rate change and the outcomes of interest. In particular, if the Insurer increased monitoring of services with larger rate increases this could potentially affect service volumes and patient charges. Table A1 shows there is no evidence for differential changes in the share of claims rejected, a proxy for monitoring, by rate change.

4 Results

4.1 Evidence of Coding Manipulation

The data show striking changes in the composition of claims filed by private hospitals immediately after reimbursement rates are revised. Figure 2 plots the weekly composition of claims filed for the vaginal deliveries, c-section deliveries, neonatal care, and ear procedures clusters. After remaining relatively stable over the 6 months pre-reform, the composition of each cluster changes within the first week of the December 2017 reform. For example, the share of vaginal deliveries coded as "Vaginal + episiotomy" drops from 50% to 40%, while the share coded as "Basic vaginal deliveries" increases from about 15% to 25% and "Vaginal +3ANC" increases from <1% to 9%. Neonatal care claims were split roughly equally across the basic, specialized, and advanced service codes in 2017, but after the reform 50% were basic and 20% advanced.

To examine how these compositional changes relate to rate changes across all services, Table 2 presents DID estimates of the effect of a change in the reimbursement rate for a service on its share of cluster claims (the same outcome as on the y-axis in Figure 2) in Column 1 and on the log of hospital monthly service claims in Column 2 (Figure 3 presents the event study analyses of the same outcomes). They confirm that the observed changes in the composition of claims are driven by increases in claims for services with larger rate increases: a 1% increase in the reimbursement rate for a service induces a 0.2% increase in its volume share and a 0.4% increase in its claim volumes at private hospitals. Column 3, which presents effects on log claims with two separate interaction terms for positive and negative rate increases (in absolute values), indicates that this composition change is not driven purely by increases in total service volumes, but that hospitals reduce claims for services with rate decreases. Rate changes have no such effect on the composition of services at public hospitals, which do not have a financial incentive to increase revenues (Figure A3).[8]

There are three possible explanations for the increase in claims for services that are more prof-

[8]Public hospital funding is determined by annual budgets and not tied to BSBY reimbursements (the bulk of the reimbursements are not allowed to be spent by hospitals and go back to the government). Therefore, public hospital staff do not gain financially from manipulating coding to increase hospital reimbursements or from attracting more patients.

itable after the reimbursement reform: hospitals could attract patients needing these services and turn away those needing less profitable ones (patient selection), they could provide these services without any change in patient health needs (under- or over-provision), and they could file claims for these services without any change in patient need or the care they actually provide (coding manipulation). Surveys provide direct evidence of changes in coding manipulation, or in "upcoding".

To test for upcoding, patient survey data can be used to examine whether patients confirm having received the service claimed by the hospital (versus a different service). While patient self-reported confirmations are likely to be noisy and may not accurately measure *levels* of coding manipulation, their accuracy should not change discontinuously with the reimbursement reform. Therefore, *changes* in the confirmation rate for a service indicate a change in the underlying accuracy of the claims data: a decrease in the survey confirmation rate indicates coding manipulation in that service-code increased, and vice versa for an increase in the confirmation rate.

Table 3 tests the effect of the reimbursement rate change on the survey confirmation rate. The analysis focuses on vaginal and c-section deliveries, as these were the only services for which patients could reasonably be expected to provide sufficient and reliable information in the survey to distinguish between the service-codes within the cluster.[9] Column 1 confirms that an increase in the rate for a service increases its share of total cluster claims in this sub-sample (as it does in Table 2). Column 2 shows that it also decreases the likelihood that the service-code filed by the hospital in the claims data was confirmed in the survey. This aligns exactly with upcoding incentives: the more the rate of a service increases (relative to other services), the greater the reward to upcoding into it; as upcoding increases, the survey confirmation rate decreases.[10] Changes in survey confirmation explain 15% to 75% of the service volume changes across childbirth services, but these estimates may not apply to other BSBY services,

[9]For example, it is unlikely that patients can distinguish between a tympanoplasty and a mastoidectomy (closely related minor ear operations). The vaginal delivery cluster includes codes for "basic vaginal", "vaginal + forceps", "vaginal + episiotomy/tear repair", "vaginal + forceps", "vaginal + tubectomy", "vaginal + pre-eclampsia management", and "vaginal + 3 antenatal care visits" service codes; the c-section delivery cluster includes "basic c-section", "c-section + tubectomy", "c-section + pre-eclampsia management", and "c-section + 3 antenatal care visits" service codes. We were able to include survey questions to verify all of these.

[10]Upcoding may also decrease if the rewards to doing so decrease because previously low-rate services experience larger reimbursement increases, which would still result in a negative coefficient.

as upcoding responses will depend on the service-specific reward to and difficulty of upcoding. Because claims for the cheapest, “bottom-coded” services within a cluster cannot be upcoded by definition, these services should have higher patient confirmation rates that do not change with reimbursement rate or claims composition changes; all changes in the survey confirmation rate should be driven by the other “non-bottom-coded” services. Table A2 tests and confirms that this is the case.

This evidence of upcoding does not rule out the possibility that the observed changes in claims composition also reflect “real” changes in services provided. Patient selection is unlikely to be a key mechanism, as it is implausible that hospitals can ex ante identify and attract patients in need of the specific services with larger rate increases with such speed and specificity, but hospitals may change the services they provide without underlying changes in patient need. Whether the changes constitute over- or under-provision depends on whether the service was previously being adequality provided. This is discussed further in Section 4.2, where real service change can be clearly disentangled from upcoding changes.

4.1.1 No Coding Manipulation Across Clusters

The upcoding results above make it difficult to estimate service volume responses, because “real” volume changes are difficult to disentangle from upcoding changes. However, if upcoding is limited to services within the same cluster and does not occur across clusters, changes in claims volumes at the cluster level can be interpreted as a ”real” supply response.[11]

There are several reasons to believe upcoding is limited to closely-related services. First, because the Insurer randomly reviews detailed supporting documentation filed by hospitals (test results, x-rays and MRIs, medical notes etc), the likelihood of fraud detection increases as the difference in terms of symptoms and procedures between the provided and upcoded services increases. For example, a “basic vaginal” delivery is easy to upcode as a “vaginal + episiotomy” delivery, for which the only proof required is the doctor’s notes, but not as an ear surgery, which requires an x-ray, audiogram, and completely different operation notes to be submitted with the claim. Second, manipulation across clusters would require coordination across com-

[11]Conducting the analysis at the cluster level also accounts for the possibility that hospitals cost-share across related services within the same department.

pletely different departments that are often in different locations within the hospital. Field visits indicate that coding decisions are made by the medical staff in the department and that all staff within a department have a list of the BSBY service-codes and reimbursement rates for procedures done in their department, making it easy for them to upcode across services provided by their department but not those provided by other departments. Third, the majority of BSBY hospitals are relatively small and focus on certain specialties, such as maternity care or otolaryngology, and would be likely to be caught if they filed claims for other specialties, as the Insurer explicitly checks this.[12]

Patient surveys provide empirical support. Column 5 in Table 3 reports survey confirmation, similar to that used to test for upcoding in Section 4.1, but at the cluster-level. Specifically, it reports the effect of the cluster-level rate change on an indicator for whether the cluster was confirmed by the patient survey. Surveys confirmed the coded cluster 96% of the time in the pre-reform period and this does not change in response to the cluster-level reimbursement rate change even though cluster volumes change, as will be shown in Section 4.2). Therefore, the remaining analysis of effects on service volumes and patient charges is conducted at the service-cluster level using the cluster rate change as the treatment, as discussed in Section 3.4.

4.2 Effect of Increased Reimbursements on Service Volumes

Table 4 presents the effect of the cluster rate change on hospital reimbursements and claims volumes (Figure 4 presents event-study results). The administrative claims data are collapsed to create observations at the hospital-cluster-month level and regressions are weighted by the hospital's pre-reform average monthly cluster volume. An INR 1,000 increases in the cluster rate induces a more than equivalent INR 1,687 increase in the average hospital reimbursement (reflecting the change in the composition of clusters towards higher-reimbursed services discussed in Section 4.1), and an 8.8% increase in claims. Put differently, a 1,000 INR increase in reimbursements paid out by the government increases volumes by approximately 5.2% (.088/1.687*100), which implies a supply elasticity with respect to reimbursement increase of approximately 0.44

[12] It is common for the US-based literature to assume that upcoding is restricted to closely-related services for similar reasons (e.g. Dafny 2005).

(.052/(1000/8385). Unweighted estimates in Table A3 are smaller, indicating that the supply response is largely driven by higher-volume hospitals.

One possibility is that private hospitals are simply drawing patients away from public hospitals, particularly given that BSBY coverage of childbirths was discontinued at public hospitals after the reform. Table A4 shows volume changes at private and public hospitals for all services excluding childbirths. Claims increase by 7.6% at private hospitals, indicating that childbirths are not driving all the volume increase observed in Table 4, and there is no decrease in public hospital claims that would suggest substitution. Another concern is that this simply reflects an increase in "ghost" patients. However, Table A5 indicates that the cluster rate change had no effect on the likelihood of reaching a household for survey, confirming the presence of the patient sampled from the claims data, or starting the survey that would support this interpretation.

The welfare effects of these changes in provision are ambiguous. Surveys show no change in patient prior health risk or demographics (Table 7), suggesting that hospitals are changing what they provide without any substantial change in patient composition or health need. An increase in service volume may be over-provision if it was previously adequately provided, or an increase in needed care if it was previously under-provided. Although detailed data on health outcomes are not available (but surveys do not suggest major improvements or worsening in complications at or soon after the hospital visit), the supply response indicates that provider treatment decisions are responsive to government reimbursement rates. Unlike coding manipulation changes, which affect government spending, changes in service provision more directly affect patient welfare.

4.3 Effect of Increased Reimbursements on Patient Charges

If hospitals are only charging patients to compensate for reimbursement rates that are set too low to cover their costs ("balance billing"), the pre-reform OOP charges reflect the difference between the marginal cost of providing a service and the government reimbursement rate for it. When the government increases the reimbursement rate, because the cost of providing the service is unlikely to change discontinuously at the same time, we should observe an equivalent decrease in the amount hospitals charge patients, or complete pass-through. Figure 5 presents event study results showing that an increase in the cluster rate change due to the policy reform induces a large and sustained decrease in the OOP charges patients faced at hospitals. Table 5 presents DID estimates of effects on hospital reimbursement in the survey sample (as opposed to in the universe of claims as shown in Table 4) alongside the effects on patient charges. Column 1 shows that a 1000 INR increase in the cluster rate change induces a larger increase in the average reimbursement received by a hospital of INR 1,338 in the survey sample as was the case with the full claims sample. However, it leads to a significant but substantially less than equivalent decrease of INR 381 in the amount paid average. Dividing the point estimate in Column 3 by that in Column 1 indicates that the reduction in patient payments is just under 30% of the increase in hospital reimbursement, and bootstrapped standard errors allow us to reject that this share is larger than 55% with 95% confidence.

One concern with this estimate is that hospitals that were charging nothing or amounts smaller than the reimbursement increase cannot charge patients negative prices in the post-reform period. This nevertheless constitutes an over-payment to the hospital that is not reaching patients. Table A6 shows estimates for the subset of hospital-clusters that had no OOP charges in the pre-reform period in Columns 1 and 2, and estimates from Tobit specifications that adjust for bottom-censoring of the payment outcome at zero in Column 3. These are larger in magnitude than the main estimates, but are still far lower than the cluster rate change or the increase in reimbursement received by the hospital. Taking the most generous specification, the decrease in patient charges is approximately 45% of the increase in government payments that hospitals receive and bootstrapped standard errors allow us to reject a decrease larger than 70%. The analysis thus far is conservative and only examines effects on patient charges at the hospital, but not for tests or medicines purchased elsewhere. However, the hospital's BSBY reimbursement rate is supposed to cover the costs of all tests, medicines, and procedures for a visit, and requiring patients to obtain and pay for these elsewhere themselves is a potential form of capture. Estimates including patient payments for tests and medicines obtained outside the hospital in Table A7 are very similar to the main estimates.

4.3.1 Heterogeneity in Effect on Patient Charges by Market Concentration

Hospitals in more competitive markets have a greater incentive to pass through public subsidies in order to lower prices faced by patients, whereas hospitals with market power can set prices above marginal cost and may not face pressure to reduce prices or improve quality when reimbursements increase (Weyl & Fabinger 2013). Studies of Medicare Advantage find that private insurers pass through a substantially larger share of government subsidies to insurance beneficiaries in more competitive markets (Cabral et al, 2018, Duggan et al 2016). To examine heterogeneity in patient payment reductions by market power, the claims data can be used to generate two measures of pre-reform market competition. First, a Herfindahl-Hirschman Index (HHI), calculated as the sum of the squares of pre-reform market-share (BSBY claims-share is used as a proxy) of all hospitals for each service-cluster within a district. A higher HHI represents higher market concentration (lower competition). Second, a hospital density measure that is the number of hospitals filing claims for a service-cluster in a district in the pre-reform period. Measures are calculated at the district level, around which the Indian health system is broadly organized. The district administrative center is typically the largest town, where the largest public and private hospitals are located. Because these facilities serve as referral centers for smaller facilities and attract patients from across the district, analysis at a smaller unit would not capture the full market. Creating cluster-specific measures ensures that we only consider hospitals providing the same service as competitors. Using only pre-reform claims ensures that changes in concentration as a result of the policy reform do not confound our estimates. Both public and private hospital claims are included. A limitation of these measures is they do not account for non-BSBY health services or facilities.

Table 6 presents DID results, splitting the sample into below and above median HHI and hospital density. OLS regressions are presented for simplicity, but Tobit estimates show similar patterns. Reductions in patient charges are driven almost entirely by more competitive markets, using either measure of competition. These results cannot be interpreted causally, as there may be other factors correlated with competition and OOP payments. Additionally, hospital entry over the longer run may further drive down profits and patient charges, including in less competitive areas. Nevertheless, they are consistent with standard economic theory and suggest that market power shapes private hospital incentives and affects the extent to which public subsidies benefit patients. It is possible that other barriers to competition, such as high search costs and poor information on quality and prices that have been well documented in hospital health care markets may also reduce the extent to which public subsidies benefit patients rather than hospitals. Strategies to reduce market frictions and increase competition, including from a strong public sector, may improve the performance of public health insurance and warrant further study.

4.3.2 Alternate forms of pass-through

If treatment costs for the same service are heterogeneous due to patient characteristics, the marginal cost of treating a patient varies though the reimbursement does not, and hospitals benefit less from treating higher-cost patients (Dranove 1987). This creates incentives for hospitals to turn away sicker, high-cost patients with prior conditions. When reimbursement rates increase, hospitals may choose to accept these patients as another form of pass-through. Pass-through may also occur on the intensive margin in the form of higher quality, either because rate increases enable the hospital to spend more per patient or because hospitals engage in quality competition to attract patients to higher reimbursed packages.

Table 7 presents effects of reimbursement increases on several measures of patient risk, illness severity, including complications at the hospital or after discharge, and care quality in Panels A and B.[13] We report illness severity and complications in addition to patient prior risk because risk may be incompletely measured and is likely to be correlated with complications at the hospital. Furthermore, the risk outcomes are only available for the subsample of visits for childbirths. However, all of the outcomes measure aspects of care likely to increase the cost of care. We find no evidence of changes in any of these measures that would suggest hospitals accept costlier patients or increase care quality in response to the reimbursement rates.

Panel C presents effects on patient socioeconomic and demographic characteristics. Changes in these could potentially reflect unmeasured changes in patient prior risk. Furthermore, the reduction in OOP charges may draw in poorer populations. In fact, the marginal patient is

[13] Indices are computed by demeaning the component binary outcomes, normalizing by the pre-reform standard deviation, and weighting them by the inverse of the covariance matrix (Anderson 2008). They are calculated separately for each cluster to allow weights to vary depending on the service received. The variables included in each index are included in the table notes

slightly younger and wealthier, which may be because the decreases in hospital charges were not large enough to induce much poorer patients to participate in BSBY or because information about the reductions (or the program) has not reached these populations.

5 Conclusion

Lower income countries around the world are rapidly expanding public health insurance programs and contracting private hospitals for service delivery to meet the goals of universal health coverage. However, relatively little is known about how the private sector participates in these programs. This paper exploits a policy-induced change in hospital reimbursement rates to examine how private hospitals behave within a large government health insurance in India.

Increasing reimbursement rates induces large and immediate changes in claims filed for a service, due in large part to changes in coding manipulation. Hospitals also charge patients for care that is supposed to be free. Increasing service rates leads to a substantial decrease in these charges, implying that the charges were partly compensating for rates that were too low to cover costs. However, hospitals capture approximately half the increased reimbursements as profits and the decline in patient charges is driven by more competitive markets. This is consistent with evidence of monopoly inefficiencies reducing pass-through of public subsidies in other contexts (Duggan et al 2016, Cabral et al 2018). Increased reimbursement rates also induce a sizeable increase in real service volumes.

The results point to the importance of hospital reimbursement rates in shaping hospital behavior and outcomes. Increasing rates can increase hospital participation and service volumes, but may also transfer public resources to hospitals rather than benefiting patients if not accompanied by hospital monitoring. Stronger monitoring systems could help ensure hospital compliance with program rules, but need to be accompanied with efforts to rationalize reimbursement rates to accommodate local heterogeneity in input costs and reward care quality. Facilitating competition, including through stronger public sector hospitals, and increasing patient awareness of their entitlements may also be important strategies for disciplining hospitals and ensuring public subsidies benefit patients.

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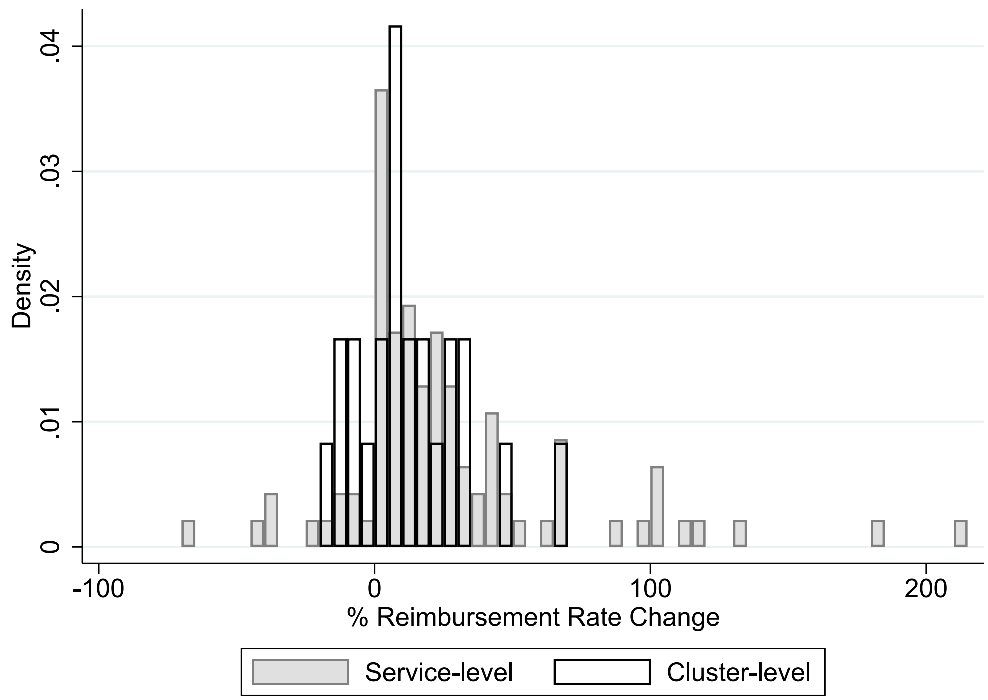
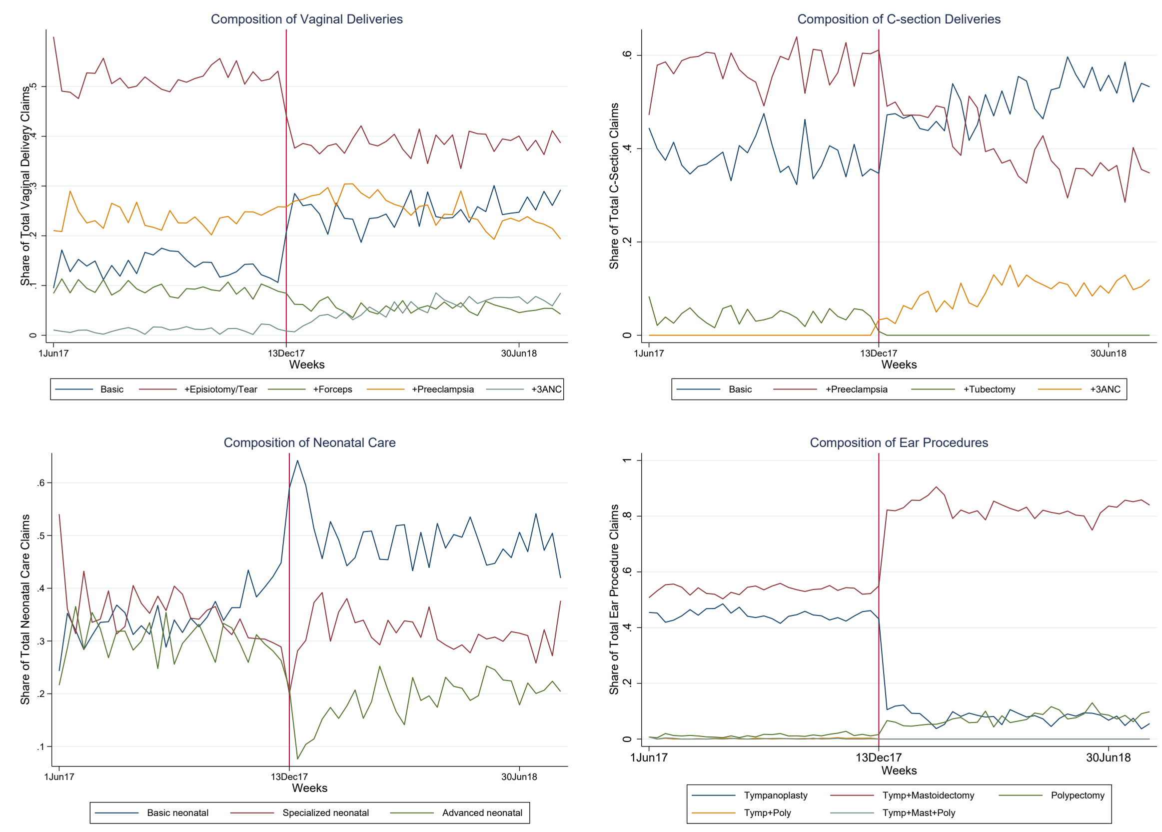
Figures

Figure 1: Variation in Service and Cluster Reimbursement Rate Change



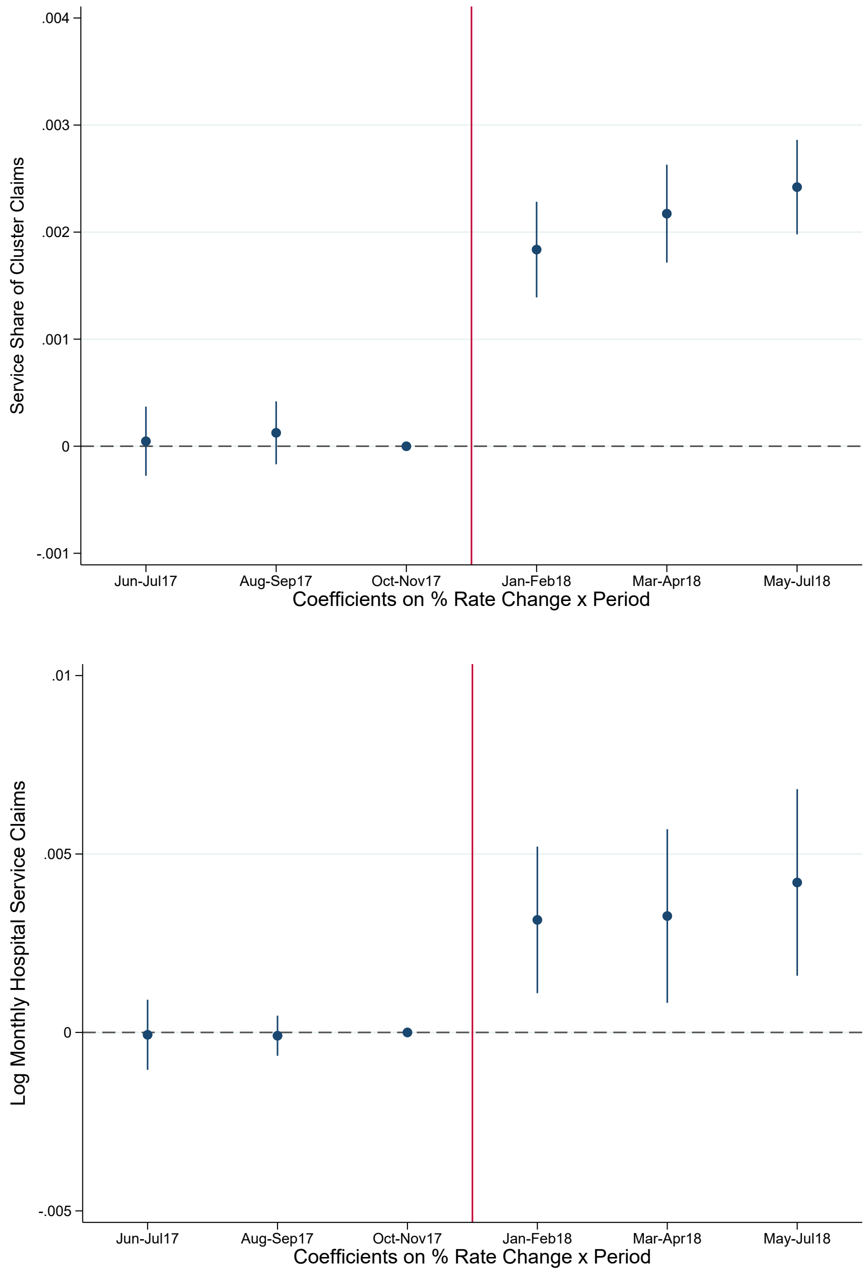
Note: The figure plots the identifying variation in the reimbursement rate change across services included in the study. The service-level reimbursement rate change is the Phase 2 rate minus the Phase 1 reimbursement rate for services. Closely related services are grouped into service-clusters, and the cluster-level reimbursement rate change is calculated as the average rate change across all services within the cluster, weighted by each service's Phase 1 claim volumes.

Figure 2: Descriptive Evidence of Changes in the Composition of BSBY Claims



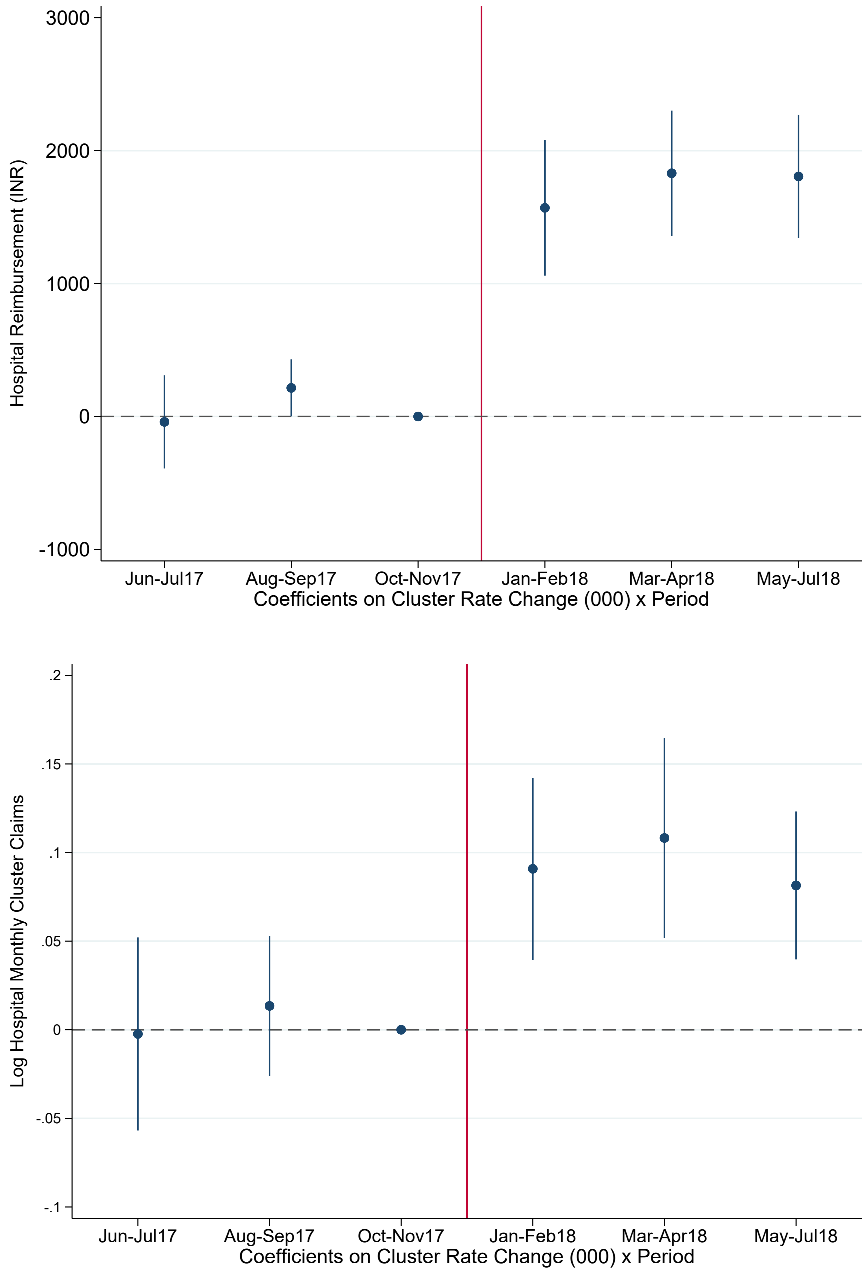
Note: The figure demonstrates the large and immediate changes in the composition of BSBY claims across different clusters observed immediately after the reimbursement rate reform that took effect on 13 December 2017. Each graph plots the weekly share of total BSBY claims within a cluster coded to each of its component service-codes. The vertical line is the date of the policy reform. The source is the administrative claims data and the sample is restricted to private hospitals that were participating in BSBY before and after December 2017. Figure A2 presents total claims (rather than shares) for the same services and clusters.

Figure 3: Event Study Effect of Rate Change on Claims Composition



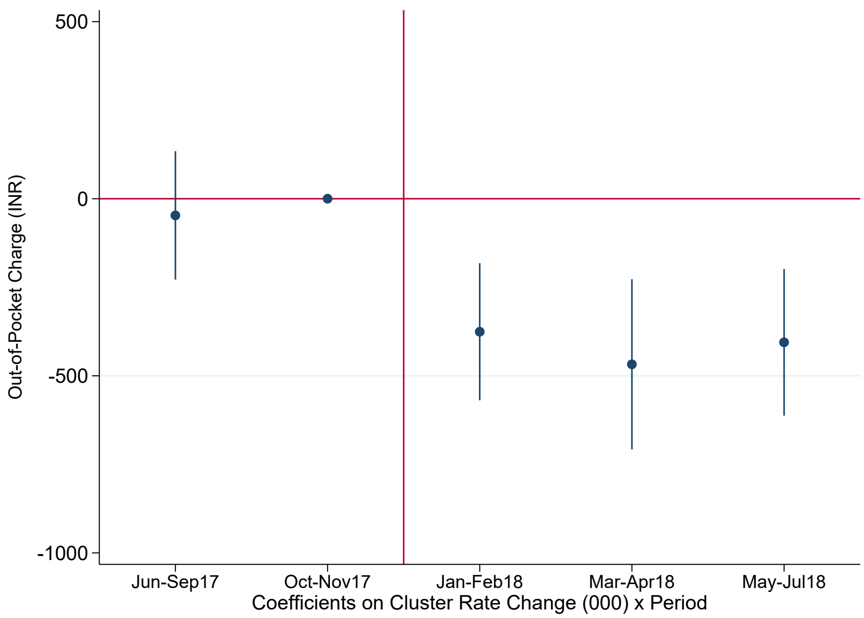
Note: The figure shows coefficients on the interaction of the service-level reimbursement rate change (in percentage terms) with two-month period dummies, from event study specifications that include month, cluster, and hospital fixed effects. October-November is the excluded reference period. The dependent variable is a hospital's monthly claims for a service as a share of its total claims in the cluster (the same as the outcome on the y-axis in Figure 2) in Panel A and the log of total hospital monthly claims for the service in Panel B. The regressions are estimated using the administrative claims data and the unit of observation is a hospital-service-month. Observations are not reweighted, so that changes in the coding behavior of small hospitals is given equal weight as those in big hospitals. % Rate Change is the percent change in the service reimbursement rate relative to its pre-reform level. The sample is restricted to the balanced panel of private hospitals that were participating in BSBY before and after December 2017. 95% confidence intervals are shown using standard errors clustered at the hospital and cluster levels.

Figure 4: Event Study Effect of Rate Change on Hospital Reimbursements and Claim Volumes



Note: The figure shows coefficients on the interaction of the cluster rate change (in thousands of Indian Rupees) with two-month period dummies, from event study specifications that include month, cluster, and hospital fixed effects. October-November is the excluded reference period and weights for pre-reform average monthly hospital cluster claim volumes are included. The dependent variable is the hospital average reimbursement for a claim in a cluster in Panel A and the log of total hospital monthly claims for that cluster in Panel B. The regressions are estimated using the administrative claims data and the unit of observation is a hospital-cluster-month. Cluster Rate Change is calculated as the average reimbursement rate change across all services within the cluster, weighted by each service's Phase 1 claim volumes. Hospital reimbursements are in Indian Rupees. The sample is restricted to the balanced panel of private hospitals participating in BSBY before and after December 2017 and the clusters they were already providing before December 2017. 95% confidence intervals are shown using standard errors clustered at the hospital and cluster levels.

Figure 5: Event Study Effect of Rate Change on Patient Out-of-Pocket Charges



Note: The figure shows coefficients on the interaction of the cluster rate change (in thousands of Indian Rupees) with two-month period dummies, from event study specifications that includes month, cluster, and hospital fixed effects, controls for survey recall period and surveyor fixed effects, and survey sampling weights. The dependent variable is the patient-reported out-of-pocket (OOP) payment for a visit collected through post-visit patient surveys. The unit of observation is the hospital visit. Cluster Rate Change is calculated as the average reimbursement rate change across all services within the cluster, weighted by each service's Phase 1 claim volumes. All payments are in Indian Rupees (INR). The sample is post-visit patient surveys between June 2017 and July 2018; December 2017 is excluded. Standard errors are clustered at the hospital and service-cluster levels and 95% confidence intervals are shown.

Tables

Table 1: Descriptive Statistics

A. Claims Data	
Total claims	1,632,837
Total reimbursement (000s INR)	4,608,291
Claims at private hospitals (%)	54.2
Reimbursements at private hospitals (%)	75.3
Total hospitals	1,398
Private hospitals	918
B. Patient Survey Data	
Total surveys	19,705
Surveys for private hospital visits	18,600
Total hospitals	1,012
Private hospitals	734
C. Private Hospital Statistics (Jun-Dec 2017)	
Claims	383,434
Mean reimbursement per claim (INR)	9,059.9
Hospitals	651
Mean monthly claims per hospital	102
Surveys	4,831
Hospitals covered in surveys	511
Hospitals with any OOPC (%)	87.5
Patient Out-of-Pocket Charges (OOPC)	
Any patient OOPC (%)	41.4
Mean OOPC amount (INR)	2,151.0
OOPC markup on BSBY reimbursement (%)	36.5
Did not know cost before visit (%)	46.1
Paid full amount up-front (%)	48.7
Currently knows BSBY should be free (%)	47.5
Patient Characteristics	
Female (%)	71.3
Years of education	5.7
Low caste/tribal (%)	30.8
Household has a motorized vehicle (car/bike %)	32.4
Household has any vehicle (car/bike/cycle %)	53.0
Household has Cooler (%)	25.1
Household has any cooling (Cooler/fan %)	76.4

Notes: The table presents summary statistics on all claims filed over the study period (Jun2017-Jul2018) at public and private hospitals for study services (approximately 70% of total claims) in Panel A. Claims were sampled for post-visit patient surveys conducted 2-3 weeks later. Panel B reports on all patient surveys conducted, including the small sample of pre-reform surveys for public hospital visits. Panel C reports on the subset of claims and surveys for private hospitals in the pre-reform period (Jun2017-Dec2017) in Panel C.

Table 2: Effect of Rate Changes on Claims Composition

	(1) Service Share of Cluster Claims	(2) Service Claims (Log)	(3) Service Claims (Log)
% Rate change x Post	0.002*	0.004**	
	(0.001)	(0.001)	
% Pos rate change x Post			0.002*
			(0.001)
% Neg rate change x Post			-0.010**
			(0.004)
Month FE	X	X	X
Service FE	X	X	X
Hospital FE	X	X	X
Observations	43787	64688	64688
Pre-reform mean	0.520	0.974	0.974

Note: The table shows coefficients on the interaction of the service rate change (in percentage terms) with a post-reform dummy from a difference-in-differences specification with month, cluster, and hospital fixed effects. Column 3 reports coefficients on two separate interactions, of positive rate change and negative rate change, with the post-reform dummy. The absolute value of the change is used in the negative interaction, so that the coefficient is interpreted as the effect on the outcome for each percent decrease in the rate. The dependent variable in Column 1 is a hospital's claims for a service as a share of its total claims in the cluster (the same as in Figure 3 and as the outcome on the y-axis in Figure 2), and in Columns 2 and 3 it is the log of hospital monthly claims for a service. The regressions are estimated using the administrative claims data and the unit of observation is a hospital-service-month. Observations are not reweighted, so that changes in the coding behavior of small hospitals is given equal weight as those in big hospitals. % Rate Change is the percentage change in the reimbursement rate for each service between Phase 1 and Phase 2. The sample is restricted to the balanced panel of private hospitals that were participating in BSBY before and after December 2017. Standard errors clustered at the service and hospital levels are in parentheses.

Table 3: Changes in Patient Survey Confirmation of Claimed Service Codes

	Childbirth Services		All Services
	(1)	(2)	(3)
	Service Share of Cluster Claims	Claimed Service Confirmed by Survey	Claimed Cluster Confirmed by Survey
% Rate change x Post	0.004*	-0.003***	
	(0.002)	(0.001)	
% Cluster Rate Change x Post			0.001
			(0.001)
Month FE	X	X	X
Service FE	X	X	
Hospital FE	X	X	X
Cluster FE			X
Observations	10247.00	6598.00	14606.00
Pre-reform mean	0.43	0.81	0.96

Note: To test for changes in upcoding across services, the table tests whether the rate change for a service changes the likelihood that the patient confirms having received it (versus another service). The analysis in Columns 1 and 2 is restricted to claims for childbirths, for which patients can reliably report sufficient detail to distinguish between the service-codes within each cluster. Column 1 uses claims data at the hospital-service-month level and the dependent variable is a hospital's claims for a service as a share of its total claims in the cluster (as in Table 2 Column 1, but estimated on the childbirths subsample). Column 2 uses survey data at the hospital visit level and the dependent variable is a dummy for whether the service-code filed by the hospital in the claims data was confirmed in the survey. Both columns report coefficients on the interaction of the service rate change (in percentage terms) with a post-reform dummy from a difference-in-differences specification with month, service, and hospital fixed effects, and controls for survey recall period, surveyor fixed effects, and survey sampling weights in Column 2. Column 3 tests for upcoding across clusters using the full survey data on all clusters. The dependent variable is a dummy for whether the cluster filed in the claims was confirmed by survey, and coefficients on the interaction of the cluster rate change (in percentage terms) with a post-reform dummy from a difference-in-differences specification with month, cluster, and hospital fixed effects. Cluster Rate Change is calculated as the average reimbursement rate change across all services within the cluster, weighted by each service's Phase 1 claim volumes. The analysis is restricted to private panel hospitals participating in BSBY before and after December 2017. Standard errors clustered at the cluster and hospital level are in parentheses.

Table 4: Effect of Rate Change on Hospital Reimbursements and Claim Volumes

	(1) Hospital Reimbursement	(2) Cluster Claims (Log)
Cluster rate change (000s) x Post	1687.331***	0.088***
	(430.881)	(0.019)
Boot-strapped p-value	0.022	0.004
Month FE	X	X
Cluster FE	X	X
Hospital FE	X	X
Observations	37492	37492
Pre-reform Mean	8385.145	598.433

Note: The table shows coefficients on the interaction of the cluster rate change (in thousands of Indian Rupees) with a post-reform dummy from a difference-in-differences specification with month, cluster, and hospital fixed effects, and weights for pre-reform average monthly hospital cluster claim volumes. The dependent variables are the hospital average reimbursement for a claim in a cluster and the log of total hospital monthly claims for that cluster. The regressions are estimated using the administrative claims data and the unit of observation is a hospital-cluster-month. Cluster Rate Change is calculated as the average reimbursement rate change across all services within the cluster, weighted by each service's Phase 1 claim volumes. Hospital reimbursements are in Indian Rupees. The sample is restricted to the balanced panel of private hospitals participating in BSBY before and after December 2017 and the clusters they were already providing before December 2017. Standard errors clustered at the hospital and cluster levels are in parentheses. Wild cluster bootstrapped p-values are also presented.

Table 5: Effect of Rate Change on Patient Out-of-Pocket Charges

	(1) Hospital reimbursement	(2) Any Patient OOP Charge	(3) Patient OOP Charge Amount
Cluster rate change (000s) x Post	1338.090**	-0.016**	-381.291***
	(436.742)	(0.006)	(85.565)
Boot-strapped p-value	1.000	1.000	1.000
Month FE	X	X	X
Cluster FE	X	X	X
Hospital FE	X	X	X
Observations	14767	14767	14767
Pre-reform mean	10977.09	0.40	1980.56

Note: The table shows coefficients on the interaction of the cluster rate change (in thousands of Indian Rupees) with a post-reform dummy from a difference-in-differences specification that includes month, cluster, and hospital fixed effects, controls for survey recall period and surveyor fixed effects, and survey sampling weights. The dependent variable is the hospital reimbursement received for a visit recorded in the claims data in Column 1, and the likelihood and amount of patient-reported out-of-pocket (OOP) payment for that visit collected through post-visit patient surveys in Columns 2 and 3. The unit of observation is the hospital visit. Cluster Rate Change is calculated as the average reimbursement rate change across all services within the cluster, weighted by each service's Phase 1 claim volumes. All amounts are in Indian Rupees. Standard errors clustered at the hospital and cluster levels are in parentheses. Wild cluster bootstrapped p-values are also presented. The change in patient charges (Column 3) is 30% of the change in hospital reimbursement (Column 1) and the bootstrapped standard error allows us to reject that this share is larger than 55%.

Table 6: Heterogeneity in Effect on Patient Charges by Market Concentration

	Dependent Variable: Amount OOP Charge			
	(1)	(2)	(3)	(4)
	Below Median HHI	Above Median HHI	Above Median Hospital Density	Below Median Hospital Density
Cluster rate change (000s) x Post	-460.928**	-122.786	-458.271***	-138.469
	(125.519)	(104.791)	(103.347)	(114.482)
Boot-strapped p-value	0.007	0.302	0.036	0.341
Month FE	X	X	X	X
Cluster FE	X	X	X	X
Hospital FE	X	X	X	X
Observations	8097	7662	7667	8089
Pre-reform mean	2002	1813	1901	1933

Note: The table shows the effect of the cluster rate change on patient out-of-pocket (OOP) charges separately by high and low market concentration. The regression specifications are the same difference-in-differences specifications as in Table 5, estimated on subsamples of the survey data based on whether the observation has a below or above median Herfindahl-Hirschman Index (HHI) value or below or above median hospital density value. The HHI is the sum of the squares of each hospital's market share, proxied by its share of total pre-reform BSBY claims (including those filed by public hospitals), calculated separately for each cluster in each district (market). The HHI takes a value between 0 and 1, where 1 represents a single monopolistic hospital, or complete concentration. Hospital density is the pre-reform number of hospitals that filed claims for a cluster in the district as an alternative measure of concentration. Therefore, columns 1 and 3 are the higher competition subsamples and columns 2 and 4 are the lower competition subsamples. All other details are the same as in Table 5.

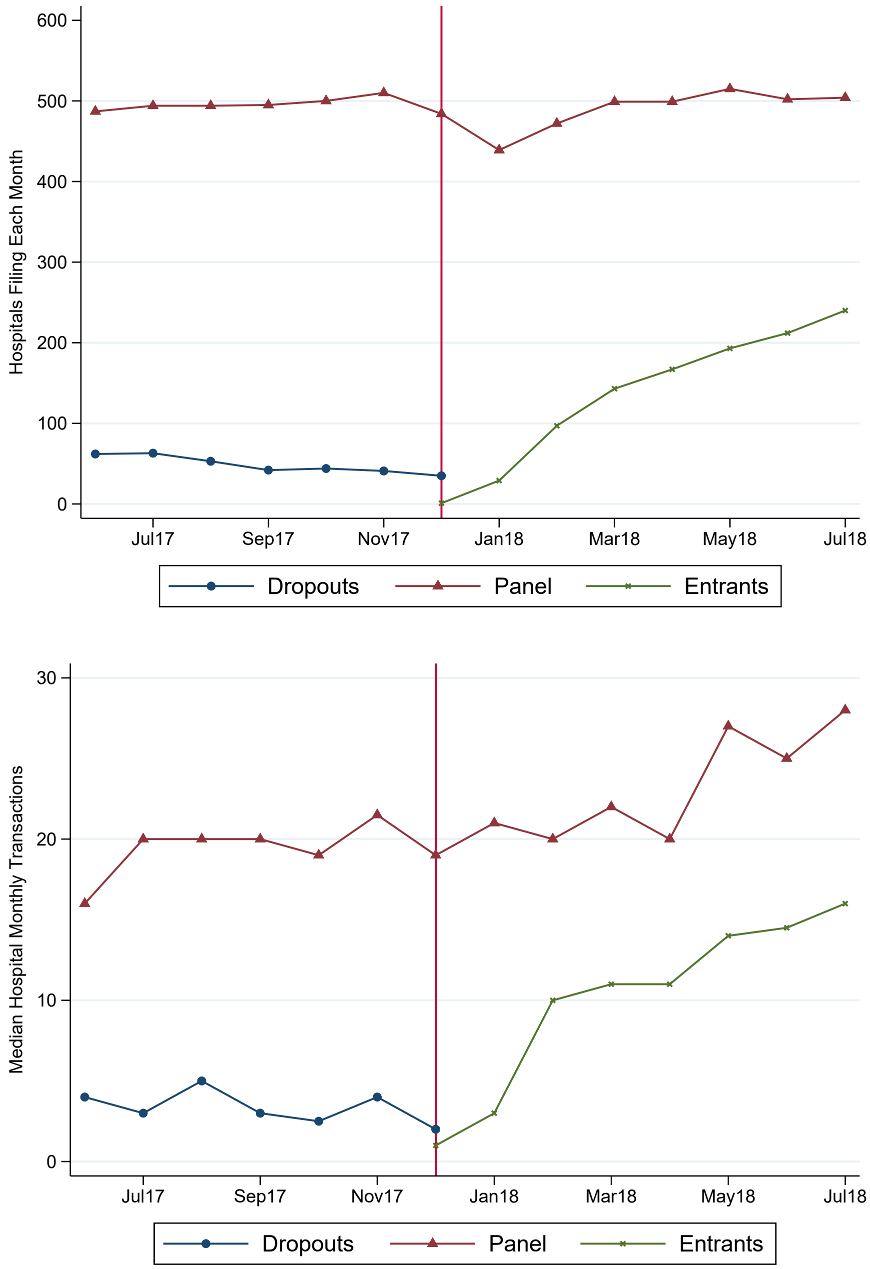
Table 7: Effect of Rate Change on Patient Risk, Care Quality, and Demographics

	(1) Risk Index	(2) Complications at hospital Index	(3) Post-visit complications Index	(4) Referred from elsewhere
Cluster rate change (000s) x Post	0.075	0.018	0.005	0.006
	(0.036)	(0.047)	(0.007)	(0.005)
Observations	6478	6659	15357	15417
Pre-reform mean	-0.02	-0.00	-0.04	0.42
	Length of Stay	Technical quality Index	Luxury Index	Perceived quality Index
Cluster rate change (000s) x Post	0.010	0.011	0.020**	0.010
	(0.024)	(0.019)	(0.009)	(0.014)
Observations	15635	15375	15119	14112
Pre-reform mean	2.50	-0.01	-0.01	-0.01
	Age	Asset Index	Schooling (std)	Low Caste
Cluster rate change (000s) x Post	-0.616**	0.026*	-0.012	-0.005
	(0.250)	(0.015)	(0.019)	(0.007)
Observations	15855	15068	15851	13865
Pre-reform mean	33.00	0.01	0.01	0.31

Note: The table shows the effect of the cluster rate change on measures of patient prior health risk and complications, care quality and intensity, and patient demographic and socioeconomic characteristics. The regression specifications are otherwise the same as in Table 5. Referral from elsewhere typically occurs when a patient has complications that a lower-level facility cannot handle. Length of stay is the number of nights spent at the hospital. Low caste is a dummy for whether the patient is from a scheduled caste or tribe. Indices are computed separately for each service by demeaning the outcomes, normalizing by the pre-reform standard deviation, and weighting by the inverse of the covariance matrix (Anderson 2008). The risk and complications measures (columns 1 and 2) are only available for childbirth visits. The outcomes included in each index are as follows: Risk: prior high BP, warning of pre-eclampsia in ANC, last pregnancy over 10 years ago, prior stillbirth, and prior c-section. Complications at the hospital: multiparous birth, heavy bleeding, fainting, convulsions, and placenta complications. Post-visit complications: a list of complications such as infection, bleeding, fever, and death of patient (and of the child for childbirths). Technical quality: seen by a doctor, was informed of dangerous symptoms, and was followed up on; for deliveries it also includes labor companion allowed and skin to skin care encouraged. Luxury: own bed, private room, and air-conditioning. Perceived quality: staff were very respectful, facility very clean, patient very satisfied with care, and would recommend the facility to others. Years of schooling is standardized to the pre-reform mean.

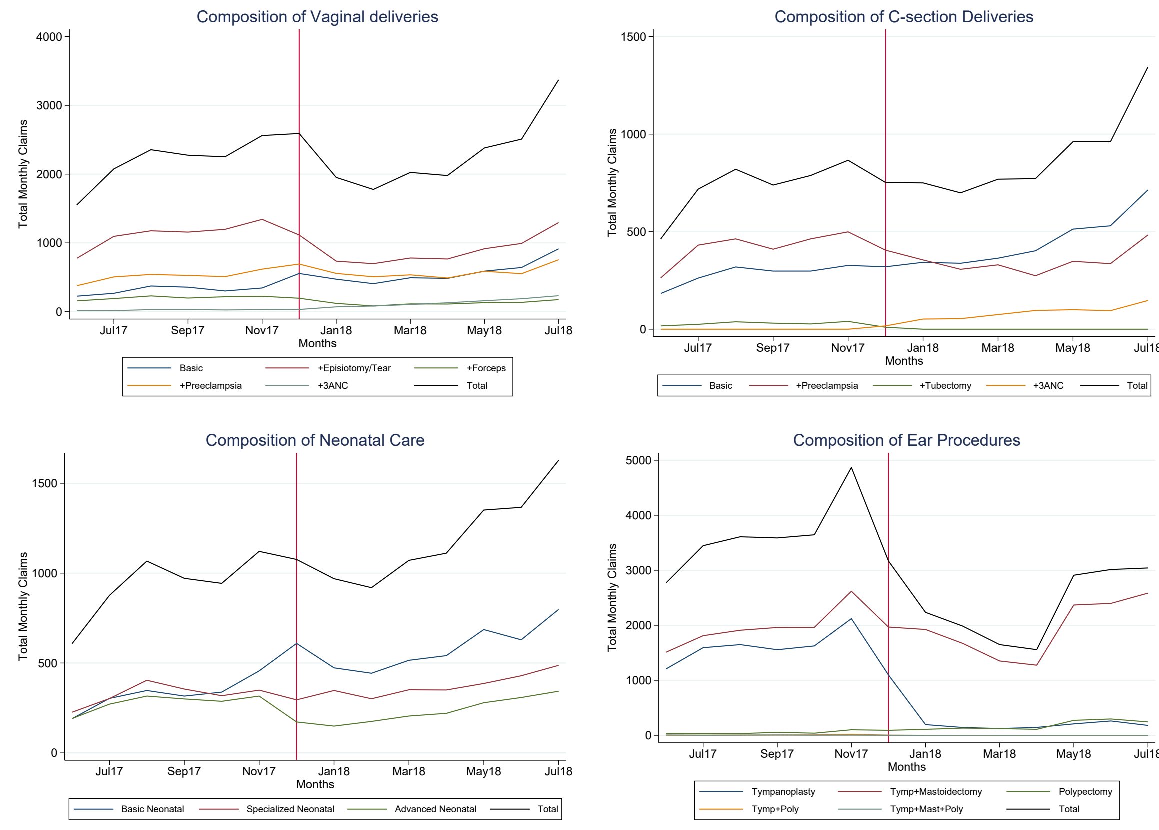
Appendix

Figure A1: Hospitals and Transactions in the Study Sample



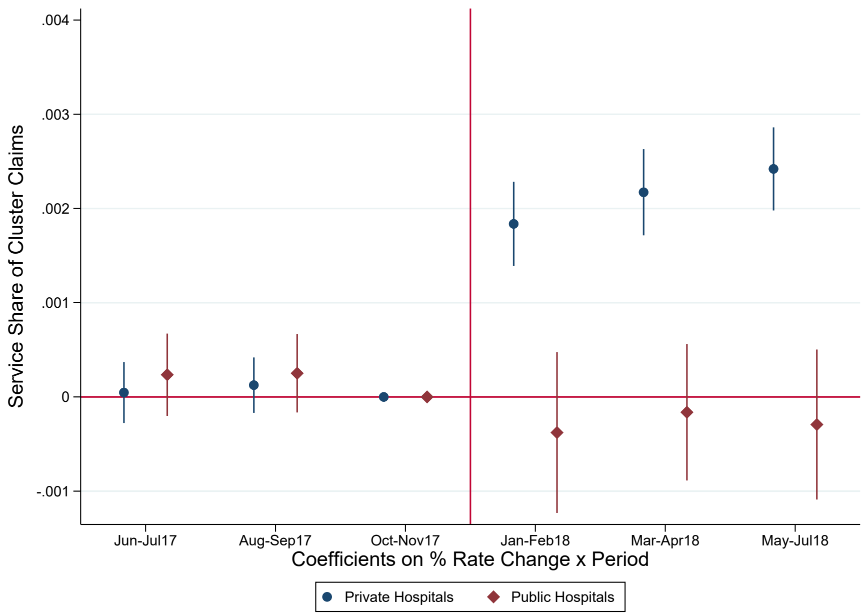
Note: Hospitals are classified as "Panel" if they filed claims before and after December 2017; as "Dropouts" if they last filed in or before December 2017; and as "Entrants" if they first filed in or after December 2017. The sample is restricted to services included in our study. Panel A presents the monthly number of hospitals filing claims, Panel B presents total monthly transactions, and Panel C presents the monthly median hospital transaction volume.

Figure A2: Descriptive Changes in the Composition of BSBY Claims Filed



Note: The figure demonstrates the large and immediate changes in the composition of BSBY claims observed immediately after the reimbursement rate reform. Each graph plots the total monthly claims for each service within the cluster. The vertical line is the date of the policy reform. The source is the administrative claims data and the sample is restricted to private hospitals that were participating in BSBY before and after December 2017. Figure fig:volshare presents service claims as a share of cluster claims (rather than totals) for the same services and clusters.

Figure A3: Event Study Effect of Rate Change on Public Hospital Claims Composition



Note: The figure shows coefficients on the interaction of the service-level reimbursement rate change (in percentage terms) with two-month period dummies, from event study specifications that include month, cluster, and hospital fixed effects. October-November is the excluded reference period. The dependent variable is a hospital's monthly claims for a service as a share of its total claims in the cluster. Regressions are identical to those in Figure 3, but are additionally estimated on public hospital claims. Because BSBY coverage of childbirths at public hospitals was discontinued in Phase 2, after the reimbursement reform, childbirth claims are excluded from both samples. All other details are the same as in Figure 3.

Table A1: Effects of Rate Change on Claims Rejections

	(1) Share of claims rejected	(2) Share of claims rejected
Service Rate Change x Post (000)	-0.000	
	(0.005)	
ctpredrc$_{x}post$		0.001
		(0.007)
Post dummy	X	X
Service FE	X	X
Cluster FE	X	X
Hospital FE	X	X
Observations	32050	24430
Pre-reform Mean	0.036	0.035

Note: The table shows the effect of reimbursement changes on claim rejection rates as a proxy for the level of monitoring. It shows coefficients on the interaction of the service rate change (in thousands of Indian Rupees) with a post-reform dummy from a difference-in-differences specification with month, service, and hospital fixed effects in Column 1 and the corresponding cluster-level specification in Column 2. The dependent variable is the share of claims rejected by the Insurer. The regressions are estimated using the administrative claims data and the unit of observation is a hospital-service-month and hospital-cluster-month in Columns 1 and 2 respectively. The sample is restricted to the balanced panel of private hospitals participating in BSBY before and after December 2017 and the services/clusters they were already providing before December 2017. Standard errors clustered at the hospital and service or cluster levels are in parentheses.

Table A2: Changes in Patient Survey Confirmation: Excluding Non-Bottom-Coded Claims

	All Childbirth Services		Excluding Bottom-Coded	
	(1)	(2)	(3)	(4)
	Service Share of Cluster Claims	Claimed Service Confirmed by Survey	Service Share of Cluster Claims	Claimed Service Confirmed by Survey
% Rate change x Post	0.004*	-0.003***	0.006**	-0.005*
	(0.002)	(0.001)	(0.001)	(0.002)
Month FE	X	X	X	X
Service FE	X	X	X	X
Hospital FE	X	X	X	X
Cluster FE				
Observations	10247.00	6598.00	6644.00	4524.00
Pre-reform mean	0.43	0.81	0.43	0.74

Note: To test for changes in upcoding across services, the table tests whether the rate change for a service changes the likelihood that the patient confirms having received it (versus another service). The table tests for upcoding by examining the effect of the rate change on claims composition and patient confirmations as in Table 3. Columns 1 and 2 are exactly as in Table 3. Columns 3 and 4 exclude the cheapest "bottom-coded" services in each cluster, which cannot be upcoded into by definition. This allows us to examine whether the survey confirmation effects are driven by non-bottom-coded services, as would be expected if they reflect upcoding. All other details are the same as in Table 3.

Table A3: Unweighted Estimates of Effect on Hospital Reimbursements and Claim Volumes

	Weighted		Unweighted	
	(1)	(2)	(3)	(4)
	Hospital Re-imbursement	Cluster Claims (Log)	Hospital Re-imbursement	Cluster Claims (Log)
Cluster rate change (000s) x Post	1687.331***	0.088***	1011.351**	0.033*
	(430.881)	(0.019)	(299.921)	(0.017)
Boot-strapped p-value	0.022	0.004	0.063	0.135
Post dummy	X	X	X	X
Cluster FE	X	X	X	X
Hospital FE	X	X	X	X
Observations	37492	37492	37492	37492
Pre-reform Mean	8385.145	598.433	8385.145	598.433

Note: The table shows the effect of the cluster rate change on hospital reimbursements and claim volumes from the same difference-in-differences specifications as in Table 4. Columns 1 and 2 include weights for pre-reform average monthly hospital cluster claim volumes and are identical to those reported in Table 4. Columns 3 and 4 report unweighted estimates for comparison. All other details are the same as in Table 4.

Table A4: Effect of Rate Change on Private and Public Hospital Claim Volumes

	Log Claims (Excluding Childbirths)		
	(1) Private	(2) Public	(3) Total
Cluster rate change (000s) x Post	0.076**	-0.057	0.060*
	(0.025)	(0.085)	(0.032)
Boot-strapped p-value	0.038	0.705	0.150
Month FE	X	X	X
Cluster FE	X	X	X
Hospital FE	X	X	X
Observations	30524	10075	40599
Pre-reform Mean	35.735	35.735	35.735

Note: The table shows the effect of the cluster rate change on claim volumes from the same difference-in-differences specifications as in Table 4. The sample is restricted to private hospital claims in Column 1 (as in Table 4) and to public hospital claims in Column 2 for comparison. Because BSBY coverage of childbirths at public hospitals was discontinued in Phase 2, after the reimbursement reform, childbirth claims are excluded from both samples. All other details are the same as in Table 4.

Table A5: Effect of Rate Change on Survey Status

	(1)	(2)	(3)	(4)	(5)
	Household reached	Confirmed no patient	Survey refused	Survey started	Recall period (days)
Cluster rate change(000) x Post	0.002	0.000	0.000	-0.001	0.021
	(0.002)	(0.001)	(0.001)	(0.002)	(0.062)
Month FE	X	X	X	X	X
Cluster FE	X	X	X	X	X
Hospital FE	X	X	X	X	X
Observations	22449	22449	22463	22449	22463
Pre-reform mean	0.76	0.04	0.03	0.66	26.72

Note: Regressions use patient survey data and report the effect of the cluster rate change on the likelihood that a sampled household was reached, reported that no one in the household had visited a hospital (which would suggest hospitals are filing claims for ghost patients), refused to participate, and started the survey. Column 5 reports the recall period, or the number of days between the claim being filed (i.e. the date the patient visited the hospital) and the survey. Standard errors are clustered at the hospital and service-cluster level in parentheses. The cluster rate change is the change in rates across service-codes within a cluster, weighted by their pre-reform share of cluster claims.

Table A6: Effect on Patient Charges After Accounting for Non-Charging Hospitals

	Excluding non-chargers		Tobit
	(1)	(2)	(3)
	Hospital reimbursement	Patient OOP Charge	Patient OOP Charge
Cluster rate change (000s) x Post	1297.217**	-486.714***	-582.619***
	(513.090)	(86.396)	(161.603)
Bootstrapped p-value	0.180	0.008	0.039
Month FE	X	X	X
Cluster FE	X	X	X
Hospital FE	X	X	X
Observations	12758	12758	14802
Pre-reform mean	11445.72	1980.56	1980.56

Note: The table shows the effect of the cluster rate change on patient out-of-pocket (OOP) charges from the same difference-in-differences specifications as in Table 5. However, the samples used in Columns 1 and 2 exclude hospital-clusters that had zero OOP charges in the pre-reform period. Column 3 uses the full survey sample with a Tobit, instead of OLS, regression that accounts for bottom-censoring of the OOP charge outcome at zero. All other details are the same as in Table 5.

Table A7: Effect on Patient Charges Including Charges Outside the Hospital

	(1) Patient OOP Charge at Hospital	(2) Patient OOP Charge Elsewhere	(3) Total Patient OOP Charge
Cluster rate change (000s) x Post	-381.291***	58.867*	-322.065**
	(85.565)	(28.283)	(84.793)
Bootstrapped p-value	0.008	0.036	0.014
Month FE	X	X	X
Cluster FE	X	X	X
Hospital FE	X	X	X
Observations	14767	14737	14767
Pre-reform mean	1980.56	336.31	2158.77

Note: The table shows the effect of the cluster rate change on patient out-of-pocket (OOP) charges from the same difference-in-differences specifications as in Table 5. The dependent variable is the OOP charge paid to the hospital for a visit (the same as in Column 3 of Table 5) in Column 1, the OOP charge paid for tests and medicines associated with the same visit but obtained outside the hospital in Column 2, and the sum of the two in Column 3. The main analysis focuses on charges at the hospital. However, the hospital's BSBY reimbursement rate is supposed to cover the costs of all tests, medicines, and procedures for a visit, and requiring patients to obtain and pay for these elsewhere themselves is a potential form of capture. All other details are the same as in Table 5.