

# ESSAYS IN HEALTH ECONOMICS

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# ESSAYS IN HEALTH ECONOMICS

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## INTRODUCTION TO RESEARCH

This dissertation examines how policies and behavioral choices influence various health outcomes across multiple dimensions.

My first essay investigates whether media campaigns can alter sex-selective preferences by analyzing a novel policy intervention in India aimed at addressing skewed child sex ratios. In 2011, India's child sex ratio was observed to be significantly below natural levels due to strong preferences for male children. Responding to this crisis, the Indian government launched a comprehensive policy in 2015 designed to shift these preferences through targeted media campaigns. The intervention began in one hundred critical districts before expanding to additional areas nationwide.

I employ a regression discontinuity design that exploits the government's systematic targeting of districts with child sex ratios below the national average, allowing me to estimate the intent-to-treat effects of the campaign. The analysis reveals minimal statistical evidence of improvement in child sex ratios, which contradicts findings from previous studies.

However, since all districts received identical budgets regardless of population size, I examine the effects of per-capita investment intensity. This analysis uncovers meaningful positive impacts, particularly concentrated in districts with smaller populations that benefited from higher per-capita investment levels. These effects strengthen over time, suggesting that sustained exposure to the policy intervention may prove effective in changing deeply rooted preferences.

My second essay studies potential racial and ethnic bias that may exist in the healthcare community by examining the results of prostate-specific antigen (PSA) tests and the subsequent referral to prostate cancer screening for men of different ages and racial backgrounds.

Using a novel, proprietary medical claims dataset, I built episodes of care for up to 180 days after the initial PSA test to study the rate of referral to either a MRI or a TRUS prostate biopsy, stratified by age and race. The outcome variable is a binary indicator of whether a patient underwent either a prostate biopsy or prostate MRI within 180 days after PSA test date. This outcome was defined both for all PSA testing dates and among the subset of PSA tests that revealed an elevated PSA level. I explore three PSA levels as thresholds for elevated PSA:

- 1.) PSA level exceeding 2.5 ng/mL, a lower threshold that is now being recognized for early detection of prostate cancer
- 2.) PSA level higher than 4 ng/mL, historically considered as an appropriate level to recommend a prostate biopsy
- 3.) PSA level greater than 10 ng/mL, a threshold previously associated with high rates of prostate biopsy and a high rate of prostate cancer

Overall, I find that contrary to previous studies, disparities in follow-up PCa screening when simultaneously considering prostate biopsy or MRI are more consistent with the underlying risk of PCa by race.

In my final essay, I use multiple data sources to compare and estimate low-dose computed tomography (LDCT) screening rates between populations of insured patients by different payer types, specifically, commercial plans, Medicare fee-for-service (i.e. Part A & B), and Medicare Advantage, and for several enrollee demographic and geographic characteristics.

Under the Affordable Care Act, most insurance providers are required to provide lung cancer screenings to eligible individuals at no cost to the patients. However, these rates remain significantly low. Using proprietary claims data, data from 2017 Centers for Medicare & Medicaid Service's (CMS) 5% Research Identifiable Files (RIF) and smoking rates from the University of Wisconsin's County Health Ranking I estimate the county level LDCT screening rates.

Overall, I find that eligible Medicare Advantage members undergo LDCT at a higher rate than Medicare FFS enrollees. These rates are substantially lower for individuals that come from a non-White ethnic and racial background. Additionally, rural areas tend to have lower screening rates as compared to urban areas, despite having a larger eligible population.

# CAN AWARENESS AND MEDIA CAMPAIGNS HELP BALANCE CHILD SEX RATIO?

## 2.1 Introduction

The Child Sex Ratio (CSR) is defined as the number of girls for every one thousand boys, between the ages of zero to six years. Although the natural rate is 950 girls for every 1000 boys (Koya, 2015), practices like sex selective abortions, infanticide and neglect can alter this ratio. While son preferences are stronger in developing countries, similar trends have been observed in developed countries like the United States as well, often in the immigrant communities (Blau et al., 2019). This is a cause of concern because an unbalanced CSR can contribute to increased rates of domestic violence, human trafficking and other crimes against women (South et al., 2012; Kaur, 2013). Men also tend to suffer as imbalanced sex ratios can affect their position in the marriage market, causing stress, higher mortality and other unfavorable long-term health outcomes (Jin et al., 2010).

India has historically exhibited strong son preferences and a prevalent practice of sex-selective abortions and female infanticide. This was highlighted in the 2011 census which reported a national average CSR of 919 girls for every 1000 boys, varying anywhere between 775 and 1033 among individual districts (India, 2019), as depicted in Figure A.1. To correct this, the Government of India launched a policy, called *Beti Bachao Beti Padhao (BBBP)* (“Save the Girl Child, Educate the Girl Child”), that relied on media campaigns to reduce the bias against girl child.

I use a regression discontinuity design to evaluate BBBP's impact on CSR by leveraging the program's district selection criteria where districts were chosen for treatment if their CSR fell below specific thresholds (872 in 2015 and 892 in 2016). Using annual vital statistics from India's Civil Registration System, I analyze how the program affected districts treated across the treatment cutoff during different phases of implementation. Since each district received the same budget allocation regardless of size, I investigate whether the intensity of resources per person matters. By dividing districts into three groups based on population size, I find the program significantly improved CSR. These effects, however, are concentrated to districts with the lowest population levels, that enjoyed higher per-capita investment, as well as to districts that were exposed to the treatment for a longer period. Lastly, to assess the robustness of my findings, I conduct a series of sensitivity analyses - including placebo tests, balance tests and density tests.

This study contributes to the literature on gender equality and imbalanced sex ratios by evaluating the effectiveness of India's policy and exploring its broader causes, consequences, and potential solutions. In the Indian context, the issue of imbalanced sex ratios was brought to light by papers like Sen's "Missing women" that concluded there were about thirty-seven million missing women in India (Sen, 1992). Subsequent studies, built on this foundation, attributed the practice of dowry as a major reason for son preference (Banerjee, 2014), which was aided by the introduction of ultrasound technology in the 1970s that enabled parents to know the sex of the child before birth (Vaze, 2021). The delayed and inadequate enforcement of laws prohibiting gender-based prenatal identification led to a stark decrease of sixty-three million fewer women between the 1970s and 2017, with projections suggesting an additional seven million fewer women between

2017 and 2030 (Vaze, 2021). This paper contributes to the literature as an additional evaluation of a nationwide intervention focused on improving CSR through media advocacy.

Existing studies have analyzed both, fertility outcomes<sup>1</sup> as well as educational outcomes<sup>2</sup> of the policy. The findings of this paper, however, are in contrast with existing studies that find generally positive impacts of BBBP on female births. These differences likely stem from methodological and data considerations. While previous work relies on survey data, like the National Family Health Survey, I use administrative data from the Civil Registration System which provides comprehensive birth registration at the district level. This data source captures the universe of registered births rather than survey sample and is less susceptible to recall bias or selective reporting. Moreover, my identification strategy using regression discontinuity around specific CSR thresholds provides clean causal estimates of the policy's impact. The finding that effects are concentrated in less populated districts suggests that previous studies might be picking up effects from areas with higher per-capita program intensity, but generalizing these to all treated districts. This highlights the need for more research into how program intensity affects outcomes.

Countries besides India have also suffered from extremely imbalanced CSR, leading governments to use a variety of interventions. In South Korea, the government passed laws to make inheritance more equitable, improved government backed old-age

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<sup>1</sup> Dasgupta & Sharma (2023) study the same policy and use a triple difference strategy to find positive impact on number of females being born as the first child relative to males as well as their immediate health outcomes.

<sup>2</sup> One other current paper that studies this policy looks at educational outcomes and observes a 11% increase in enrollment for girls. These results are significantly reduced when accounting for individual characteristics etc (Mukhopadhyay et al., 2024)

pension plans (Den et al., 2015) and restricted abortions (Hesketh and Xing, 2006).<sup>3</sup> This resulted in a CSR improvement from 116.5 in 1990 to 106.2 in 2007 (Den et al., 2015). China also launched a media campaign in 2003 called “Care for Girls” in twenty-four counties (Zhou et al., 2012). Like *Beti Bachao Beti Padhao*, this policy was also rolled out in a staggered manner and employed media interventions like documentaries and posters with the aim to reduce bias against girls (Murphy, 2014).<sup>4</sup>

Given that countries like China, Vietnam, Azerbaijan, and others still suffer from extremely imbalanced CSR (World Bank, 2024), understanding effective policy interventions remains crucial. While previous studies have demonstrated that government interventions can successfully influence CSR, these have typically involved either drastic government action or small-scale programs. This paper evaluates a large-scale media campaign, with potential implications beyond sex ratios. Governments have frequently employed media campaigns to influence various behaviors, from smoking cessation (Durkin et al., 2012) to safe sex practices (Hennessy, 2013), yielding mixed results. The Indian government's \$46 million-per-year initiative therefore offers a unique opportunity to assess the impact of concentrated media efforts on shifting social behaviors. The finding that significant results emerge only in subgroups with the highest per-capita investment as well as longer exposure duration provides valuable insights for policymakers considering

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<sup>3</sup> These legal changes helped establish the identity of a woman as an individual with equal ownership of family, reduced the parental expectation that sons would support them and helped remove the stigma against raising girls (Den et al., 2015).

<sup>4</sup> The initiative was moderately successful as a 2007 survey showed a reduced son preference in the treated counties, but suffered from confounding results due to the overlapping influence of other policies (Zhou et al., 2012).

similar media-based interventions, both in addressing gender imbalance and in other domains requiring behavioral change.

The rest of the paper is structured as follows. In the next section, I discuss the background and implementation strategy of the policy followed by a discussion of the methodology and the data sources. Next, I discuss the validity of the design before presenting the results as well as concluding remarks.

## **2.2 Background**

The number of girls between the ages of zero to six years fell from 927 to 919 for every thousand boys between the 2001 and 2011 census, with some districts showing even more alarmingly low numbers. To improve this declining CSR, the Government of India launched the “Beti Bachao Beti Padhao” (Save the Girl Child, Educate the Girl Child) initiative on 22<sup>nd</sup> of January 2015 (India, 2019). The policy aimed to combat gender-biased sex selection, raise awareness about the importance of girls’ education, and address the declining CSR by implementing concentrated media and advocacy campaigns to reduce the stigma of having a girl child and altering son preferences (India, 2019). The media and advocacy campaigns incorporated diverse strategies, ranging from local theatrical productions promoting female empowerment to showcasing the district's CSR on digital boards in government offices (India, 2019). Other activities included commemorating the birth of girls through distribution of sweets and honoring families, dedicating a day each month to celebrate the girl child and encouraging reversal of son-centric customs (India, 2019). Although the policy’s guidelines also emphasize improving the enforcement of laws

prohibiting sex-selective abortions and enhancing access to education, the primary focus is on advocacy campaigns (India, 2019).

As a national level initiative, the policy was implemented through State Governments via District Collectors, with the Government of India providing hundred percent assistance (India, 2019). The allocated budget for the policy spanning from 2017 and 2020 totaled Rs.1132.5 Crores (~\$140 million), or Rs. 377.5 crore (~\$46 mil) per year, with each district receiving an annual grant of Rs.50 Lakhs (~\$60000) (India, 2019). Out of the total budget of \$140 million, approximately \$64 million was designated for central-level operations. These funds were utilized by the Ministry of Information and Broadcasting (MoIB) and the Directorate of Advertising and Visual Publicity (DAVP). They were employed for media campaigns, establishing a record-keeping system and maintaining it (India, 2019). The MoIB and DAVP used the medium of All India Radio as well as Doordarshan, the government- owned television broadcaster to run advertisements (India, 2019). While the use of radios and television for promotional purposes may potentially lead to spillover effects in untreated districts, any resulting changes would likely affect both the treated and untreated districts uniformly. Hence, these variations would be accounted for by the variable tracking time-specific fixed effects, ensuring that the analysis captures and adjusts for any common changes occurring across the districts over time.

The remaining amount was evenly distributed among the treated districts, facilitating localized awareness campaigns, activities, and media initiatives (India, 2019). Each district had to allocate sixty-six percent of its budget towards innovative outreach programs and localized media campaigns. These initiatives encompassed activities such as celebrating Girl Child Day, orchestrating street plays and rallies emphasizing the

significance of girls, running a mobile exhibition vans and investing in important resources for social workers (India, 2019). About ten lakhs (~\$12,000) of the remaining funds was split equally between promoting the education of girls<sup>5</sup> as well as ensuring an effective implementation of the Pre-Conception and Pre-Natal Diagnostic Techniques Act that prohibits sex selective abortions (India, 2019).

The first phase of the policy began in January 2015 across one hundred gender critical districts, commencing with the inaugural event in the state of Haryana (India, 2019). According to the implementation guidelines, eighty-seven districts were selected from twenty-three states and union territories where the CSR was lower than the national average. Additionally, eight districts were selected from eight states and union territories exhibiting CSR higher than the national average but with a declining trend (India, 2019). Lastly, five districts were chosen from five states and union territories that showcased not only an above average CSR but also positive trends, intended to serve as benchmarks for the rest of the nation (India, 2019). Following that, the second phase, in February of 2016, expanded the policy to sixty-one additional districts, chosen from eleven states that also exhibited a low CSR (India, 2019). Finally, in 2017, the policy was expanded to the entire nation, with each district being treated through either “multi-sectoral interventions” or by “alert media advocacy and outreach” (India, 2019). However, the expansion beyond the second phase is beyond the scope of this study. Figure A.2 illustrates the staggered rollout across the nation over time.

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<sup>5</sup> Efforts to promote education included the establishment of awards for girls that were academically meritorious as well as for schools that ensured dropout rates for girls remained low (India, 2019)

The media campaigns consisted of two distinct approaches: “multi-sectoral interventions” and “alert media advocacy and outreach” (India, 2019). The latter approach was implemented in 235 districts, after the second phase and hence, is beyond the scope of this paper. The multi-sectoral interventions covered all one hundred and sixty-one districts that were treated in phase one and phase two (India, 2019). These are the districts of interest for this paper. After the second phase, it was expanded to 244 additional districts. It involved a range of interventions, utilizing electronic media campaigns through phones, radios, and televisions as well as emphasizing on the strict enforcement of laws prohibiting the disclosure of fetal gender. Moreover, it integrated grassroots initiatives such as training local healthcare workers and organizing local events and rallies to raise awareness and initiate discussions about the issue (India, 2019). A major focus was placed on these grassroots initiatives which also used methods like a mobile exhibition van which travelled within the treated district and showed movies, documentaries and promotional video clips on women empowerment on LED screens (Excelsior, 2016). Other initiatives included displaying the current CSR of the district in government offices, celebrating “Girl Child Day” every month, honoring families where girls are born as well as government employees and volunteers that promoted women empowerment and balanced CSR(India, 2019). The primary focus of the policy was on young couples and expecting parents' families to mitigate biases against girls (India, 2019). The secondary targets encompassed medical practitioners and diagnostic centers, emphasizing the importance of ensuring the survival and well-being of female fetuses (India, 2019). Lastly, the policy aimed to engage local politicians, religious leaders and other influential figures who could potentially impact societal perceptions and behaviors (India, 2019).

### 2.3 Methodology

According to the policy guidelines, districts with a CSR of 919 or lower on children under five years of age in the 2011 census were eligible to receive treatment of being exposed to media and awareness campaigns (India, 2019). However, as shown in Figure A.3, the observed cutoff for treatment was 872 for districts treated in 2015 and 892 for districts treated in 2016. I exploit these administrative cutoffs in a Regression Discontinuity framework to estimate the intent-to-treat effects of the BBBP program by comparing outcomes between districts just below and above these thresholds. This approach identifies the causal impact of being designated for treatment, regardless of actual implementation intensity.

Regression Discontinuity Design (RDD) relies on the fundamental assumption that while treatment and control groups may differ systematically across the full range of the running variable, these differences—both in observable and unobservable characteristics—approach zero as observations converge toward the treatment threshold. This continuity assumption implies that in the absence of treatment, the relationship between the running variable and outcomes would be smooth across the cutoff point. Therefore, any discontinuity observed in outcomes at the threshold can be interpreted as the causal effect of treatment for units near the cutoff. This treatment effect identified through RDD specifically represents the local average treatment effect for units near the cutoff, and not average treatment effect for the entire population. In context of this paper, the identification strategy relies on the assumption that districts just above and below the treatment threshold, based on 2011 CSR, exhibit similar underlying attitudes toward female children and women in general. Given that these attitudes and other unobservable characteristics should

vary smoothly across the cutoff, any discontinuity in outcomes for districts near the threshold can be causally attributed to the policy intervention.

To formally validate the RDD assumptions, I conduct two key tests. First, I examine whether the number of districts changes smoothly around the cutoff point, which helps verify that districts were not strategically chosen for treatment - a concern that is already unlikely since treatment was based on census data collected four years before the program began. Second, I test whether districts just above and below the cutoff were similar before the program by comparing 2011 characteristics including female literacy rates, religious composition, economic indicators, and reported crimes against women. These characteristics should vary smoothly across districts because factors that influence gender outcomes, such as cultural norms and economic conditions, typically change gradually across geographic areas rather than showing sharp changes at administrative boundaries

The equation for the RDD is as follows:

$$CSR_{(j)} = \alpha + \beta * Treated + f(X - c) + \epsilon_{(j)}$$

Where  $X$  is the running variable, the CSR according to the 2011 census, and  $c$  is the cutoff point of 872 for districts treated in 2015 and 892 for districts treated in 2016.  $\beta$  is the variable of interest that shows the intent-to-treat effects of the policy. The function  $f(X-c)$  represents a flexible control function of the running variable, centered at the relevant cutoff, which is allowed to be flexible on each side of the treatment cutoff, fitting separate local linear regressions on each side of the threshold. The different cutoffs accounts for the

staggered nature of the policy rollout, where some districts were treated in 2015 while others received treatment in 2016. Lastly, following the current literature, I show estimates for a range of bandwidths, while highlighting estimates that use coverage error-rate optimal bandwidth (Calonico et al., 2020). This bandwidth choice minimizes the coverage error-rate of the robust bias-corrected confidence intervals and hence, is better suited for inference purposes (Calonico et al., 2017)

Due to the staggered rollout of the treatment, the cutoff points vary across the treatment years, which may lead to a contaminated comparison group. To avoid conflating these treatment waves and ensure clean identification, I employ a "donut" RD design that excludes observations between these two cutoffs. The general idea for a donut RD is that if there is any nonrandom sorting among the observations, it is likely to happen near the cutoff and thus, by excluding those observations, the RD treatment effect might change (Barreca et al., 2011). In this paper, the purpose is to ensure that the analysis compares untreated districts above 892 with treated districts below 872, allowing for clear estimation of the treatment effect without contamination from the intermediate group of districts that received treatment under different timing.

Lastly, I explore whether the effects are magnified in areas with greater per-capita funding. The program allocated identical budgets to each treated district, regardless of their population size. This created an unintended variation in per-capita funding - districts with smaller populations received more funding per person compared to more populous districts. I leverage this variation to understand how funding intensity affects program outcomes. Specifically, I divide districts into three groups based on their 2011 population size and estimate the RDD model separately for each group. This approach helps answer

whether the program had larger effects in districts that effectively received more money per person. The key advantage of using population-based variation in funding intensity is that population sizes were determined well before the program started and thus are unlikely to be related to how districts were selected for treatment.

## **2.4 Data**

### *2.4.1 Vital Statistics Data*

For this study, I utilize the Vital Statistics Data from India's Civil Registration System (CRS) spanning 2009 to 2016. The CRS represents a comprehensive national framework managed by the Government of India that systematically registers births and deaths at the district and block levels. The system operates through a dual recording method designed to ensure data accuracy and completeness, with resident enumerators stationed in each district maintaining continuous tallies of vital events while independent supervisors conduct retrospective reviews and verification processes every six months (Vital Statistics Division). This layered approach creates multiple checkpoints for data validation and helps maintain the integrity of the registration system across India's diverse administrative landscape.

The quality and coverage of the CRS data have shown marked improvement over time, reflecting both administrative enhancements and policy interventions. National reporting levels demonstrated consistent upward momentum, rising from 81% in 2009 to 86% in 2016 (Vital Statistics Division).

Historically, the registration system exhibited variations in coverage based on the circumstances of birth, with deliveries occurring in medical institutions showing significantly higher registration rates compared to home births. However, the Government of India has actively worked on bridging these gaps with targeted policies, leading to almost 90% coverage nationally in 2019-21, with a significant number of states achieving perfect or nearly perfect registration levels (Verma et al., 2024).

A critical consideration for this analysis is the potential for gender bias in birth registration, which could skew findings. However, existing research has shown that female children do not experience lower birth registration rates compared to their male counterparts (Kumar and Nandita, 2021), suggesting that the data provides a representative sample across genders. This gender parity in registration is likely influenced by policy innovations, including a conditional cash transfer program that provides financial incentives to parents for registering female births, offering Rs 500 (~\$6) per registration (Kumar and Nandita, 2021). Collectively, these characteristics establish the CRS as a robust and reliable data source for this paper.

Overall, the CRS data records comprehensive birth-related information, like total number of births, number of births by gender, the CSR at birth as well as number of births by rural-urban status. These records are published annually in PDF format by the Government of India. I construct my dataset by combining extraction tools available on AI platforms as well as manual coding to convert this data into a useable dataset<sup>6</sup>.

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<sup>6</sup> The district level data is available from 2009 onwards.

The CRS data offers several advantages over alternative sources such as the National Family and Health Survey (NFHS) that have been previously employed to study this policy. First, since birth registration is mandatory under the Registration of Births and Deaths Act, 1969, the CRS provides more comprehensive coverage compared to sample surveys. Second, the annual frequency of CRS data allows for more granular analysis of temporal variations compared to the sporadic NFHS waves. Third, as an official administrative record, it is less susceptible to recall bias and reporting errors that typically plague survey data.

The dataset, while comprehensive, presents certain limitations that necessitated careful preprocessing to ensure the validity and reliability of the results. The primary constraint here is the presence of missing observations for various district-state pairs. To account for potential anomalies in the data recording process, districts exhibiting unusually high variability in birth counts were excluded from the analysis. Specifically, I dropped any year for a district where the total number of births exceeds two standard deviations from that district's mean across all years. These steps serve to eliminate outliers that could potentially skew the results and lead to spurious conclusions. Following these data refinements, the analytical sample retains 4266 of 4350 observations, including eighty-five of the hundred districts for treatment year 2015 and fifty-two of the sixty-one districts for the treatment year of 2016<sup>7</sup>. When accounting for the optimal bandwidth, I retain forty-six

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<sup>7</sup> Because of geo-political unrest, in 2014 the state of Andhra Pradesh broke into two parts, Andhra Pradesh and Telangana (Mitta, 2013). Not only did the redrawing of state lines and renaming of districts cause identification issues but also causes issues with comparisons. Hence, these states were dropped.

of the hundred initially treated districts in 2015 and thirty-three of the sixty-one districts treated in 2016.

#### *2.4.2 Treated Districts Data*

The data on the time and place of treatment comes from the official implementation guidelines of Beti Bachao Beti Padhao found on the website for the Ministry of Women and Child Development (India, 2019). The purpose of these guidelines, as stated, is to serve as a reference on how to implement, monitor and report activities related to Beti Bachao Beti Padhao (India, 2019).

#### *2.4.3 Other Datasets*

I use other data tables from the 2011 census<sup>8</sup> to get information on district level characteristics like treatment status, total births in a year, women's education level, distribution of religions across the cutoff, crimes against women and district level population. I combine this data with the CRS data to form a comprehensive dataset that allows for analysis. Table A.1 shows the descriptive statistics for the dataset.

Given that the 2011 CSR was used to determine treatment status, these statistics provide a comprehensive summary of the difference between the treated and control districts in that year. These baseline differentials, captured in the pre-intervention year, provide crucial context for understanding the initial conditions from which treatment effects emerged. The data is organized by treatment status: control districts, districts treated in 2015, and districts treated in 2016. For each group, I report average total births, followed

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<sup>8</sup> The 2011 census data is also the most current census record right now

by a breakdown of male and female births in rural and urban areas. The CSR is calculated as the number of female births per 1,000 male births, with lower values indicating greater gender imbalance. The table shows that districts selected for treatment had worse initial gender imbalances, with CSR of 859 and 872 in the 2015 and 2016 treatment groups respectively, compared to 944 in control districts. Overall, the table indicates towards a significant difference in the number of male and female births across the control and treated districts.

## **2.5 Validity of RD**

As discussed in the previous section, the validity of a RD rests upon the assumption that all underlying characteristics are smooth across the treatment cutoff and hence, any variation observed in the outcome variable is due to the treatment status. In this section, I consider some population characteristics as well as other using data from the 2011 Census that may be of interest.

A critical concern, in general, for any regression discontinuity design is the possibility of selection into treatment where the observational units alter their characteristics to be in the treatment group (Cattaneo and Titiunik, 2022). This is not a direct concern here because of a variety of reasons. Firstly, the districts that would have been treated in the first two rounds of the policy was not public knowledge. Additionally, even if they were, since the intervention itself did not consist of any major benefits for individuals themselves, the inclination to change behaviors and have/not have a girl child solely for the intervention would have been low. Lastly, the decision to choose the cutoff for treatment was made in 2015, based on historical CSR data from 2011 census – four

years after the observed CSR, which could not be altered retroactively. Hence, it is safe to assume that districts themselves did not have the preference or the ability to choose into the treatment.

However, there is a possibility that the treatment cutoff itself was endogenously selected for a variety of reasons, like to maximize the number of districts that would receive treatment while staying within budget constraints, or to target specific districts based on political considerations rather than objective need, or even due to random chance. Although this is not a direct concern, to address this, I conduct a density test to examine the continuity of the running variable at the treatment threshold (McCrary, 2008). While this test traditionally serves to detect manipulation of the running variable by units around the cutoff point themselves it can also help assess whether the cutoff itself was strategically chosen. By showing that there is no discontinuity in the distribution of observations around the cutoff points for either treatment year (2015 and 2016), I am able to rule out concerns about endogenous selection of the treatment threshold. Figure A.8 provides evidence of no such manipulation.

Given the nature in which the policy was chosen it is unlikely that characteristics would vary sharply around the chosen CSR cutoff. Figures A.9 through A.11 present comprehensive visual and statistical evidence of pre-intervention characteristics of districts in 2011, including overall birth rates, female educational attainment, reported crimes against women, and religious composition that show the same. Each figure is structured in two panels: the first provides graphical evidence through binned means of these

characteristics across 2011 CSR, the running variable, while the second panel presents point estimates formed by local linear regressions using rectangular kernel weights, corresponding to confidence intervals across various bandwidths, with particular emphasis on the coverage error rate optimal bandwidth specification (Calonico, 2020). These point estimates test for any discontinuity observed in characteristics across the cutoffs.

The lack of significant change at the treatment threshold, insignificant discontinuity coefficients and a lack of clear relationship between the 2011 CSR and these characteristics shows that districts on either side of the treatment threshold were comparable in terms of key characteristics prior to the intervention. This suggests that any observed changes in the CSR coinciding with the onset of treatment can be attributed to the implementation of the policy, rather than to confounding factors.

## **2.6 Results**

### *2.6.1 Overall Effects*

This study employs a RD design to evaluate the impact of a policy intervention on CSR. The running variable is derived from the 2011 census data, with the analysis focusing on three distinct scenarios:

1. Districts treated in 2015, assessed in 2015 (immediate effect)
2. Districts treated in 2015, assessed in 2016 (one-year lagged effect)
3. Districts treated in 2016, assessed in 2016 (immediate effect)

The analysis of these distinct scenarios is necessitated by the complex nature of the policy's implementation. The immediate effects in 2015, lagged effects of 2015 treatment observed in 2016, and the new wave of treatment in 2016 each provide different insights into program effectiveness. Examining these scenarios separately allows for understanding both short-term responses and dynamic effects.

For districts treated in 2015 and assessed in the same year, the analysis faces questions of implementation completeness and whether immediate effects can be meaningfully measured, given the brief time frame and potential anticipation effects as districts knew about their selection in advance. The second scenario, examining districts treated in 2015 but assessed in 2016, introduces additional complexities: the analysis must account for potential contamination from newly treated 2016 districts affecting the control group, distinguish between true program effects and implementation delays. This analysis must also separate the program's dynamic effects - whether initial changes are sustained, growing, or diminishing, from broader policy changes affecting all districts in 2016. The third scenario, analyzing districts treated and assessed in 2016, presents a different context altogether – these districts were less gender critical than the ones in the first wave and implementation might have improved due to learning from the 2015 wave. Each scenario requires its own analysis with carefully defined control groups, and together they provide complementary but distinct evidence on policy effectiveness, necessitating careful interpretation of their external validity.

While the official eligibility criterion for treatment was a CSR below 919, empirical evidence reveals that the actual implementation diverged from this threshold. The observed cutoffs was 872 for districts treated in 2015 and 892 for districts treated in 2016.

Figure A.4 illustrates the discontinuity estimates for three distinct measures of treatment impact. Panel A presents a means plot with a bin size of 10 CSR points, accompanied by fitted linear regression lines according to the optimal coverage error rate bandwidth for both the continuous running variable as well as the "donut" specifications. The bandwidth was chosen as coverage error rate-optimal bandwidth is specifically designed to optimize inference by minimizing coverage errors in confidence intervals (Calonico, 2020). Panel B shows the magnitude of the discontinuity estimate for a range of bandwidths with emphasis on the coverage error rate bandwidth.

Across all outcomes, the binned means appear largely consistent across the cutoff, with no statistically significant discontinuities observed. For districts receiving treatment in 2015, the immediate impact on CSR yields a negative point estimate of -12 at the discontinuity, suggesting no contemporaneous policy effect. A large standard error (34.12) and wide confidence interval (-79.83 to 55.76) spanning zero suggest substantial uncertainty in the estimate.

Districts treated in 2016 demonstrate a similar pattern, with an estimated discontinuity of -27 CSR points in their initial treatment year as well as a large standard error.

However, districts treated in 2015 exhibit a positive discontinuity of 7.22 CSR points in 2016, corresponding to approximately a 0.77% increase. The timing of this effect aligns with the policy's biological mechanism, as pregnancies initiated after the program's implementation in early 2015 would be observed in birth outcomes the following year, given the nine-month gestational period. But since this estimate is accompanied by a standard error of 32.18 and wide confidence interval (-48.05 to 62.49) that contains zero,

it is a statistically insignificant effect with substantial uncertainty around the true impact. While the directional heterogeneity between immediate and lagged effects, specifically, the consistently negative estimates in the year of treatment contrasted with positive staggered effects, presents an intriguing pattern, the high variance and absence of statistical significance.

### *2.6.2 Investment Per-Capital Effects*

According to the official policy implementation guidelines, each district was allocated a uniform budget of Rs. 50,00,000 (~\$60,000) annually (India, 2019). Given this uniform allocation, it is reasonable to expect that the impact of the policy may vary significantly across districts. Specifically, districts with smaller populations are likely to benefit more from the policy due to a higher per capita investment, leading to potentially larger observable effects. In contrast, in more populous districts, the same amount of funding would translate into a lower per capita investment, which may dilute the policy's impact. Therefore, the variation in population size across districts could play a crucial role in explaining differences in the magnitude of the policy's effects, with smaller districts experiencing greater benefits from the same uniform budget allocation.

To empirically investigate the hypothesized heterogeneity in treatment effects based on population size, I categorize the districts into three distinct groups based on their population sizes:

1. Tercile 1: Comprises districts with the highest population levels, representing the upper third of the population distribution.

2. Tercile 2: Encompasses districts with intermediate population sizes, corresponding to the middle third of the distribution.
3. Tercile 3: Consists of districts with the lowest population levels, representing the lower third of the population distribution.

This stratification allows for a more nuanced examination of the policy's impact across varying population levels, the results for which are presented in Figure A.5, A.6 and A.7.

Figure A.5 illustrates the immediate impact of the policy intervention across three population terciles for districts treated in 2015. The analysis reveals considerable variability in point estimates, accompanied by high levels of statistical uncertainty. Tercile 3 districts, with the lowest population, exhibit the largest point estimate, with an immediate increase of 134 CSR points, equivalent to approximately a 13% improvement. This impact is also statistically significant. However, wide confidence intervals (CI: 16.21 to 252.72) suggests substantial uncertainty about the exact magnitude. The estimated effect for Tercile 2, the moderately populated districts, is considerably smaller, at 58.14 CSR points. This estimate however, is accompanied by a high standard error of 102.51, rendering it statistically insignificant. The extreme magnitude of the standard error in this case further undermines the reliability of this point estimate. Lastly, contrary to the positive point estimates in the other terciles, the most populated districts show a negative point estimate of approximately 75 CSR points, or a 7.5% decrease. However, this estimate also lacks statistical significance, inhibiting any definitive conclusions about a detrimental effect in these districts.

The observed pattern of point estimates—highest in the least populated tercile and lowest in the most populated tercile—aligns with the hypothesis of potentially stronger effects in areas with higher per capita investment. The results are provided in Table A.3.

Figure A.6 illustrates the immediate effects of the policy intervention for districts treated in 2016, stratified by population terciles. The results reveal a complex pattern of point estimates and statistical uncertainty, broadly mirroring the findings observed for the 2015 treatment cohort. Initial analysis of the least populated group, Tercile 3, shows a positive discontinuity of 97 CSR points at the cutoff. The estimates remain statistically insignificant, echoing the results from the 2015 immediate effect analysis, albeit with a smaller coefficient magnitude. Tercile 2 exhibits a discontinuity estimate of 21 CSR points, indicating a lower impact on CSR as compared to the less populated regions. However, this effect dissipates when employing a donut design, suggesting potential sensitivity to observations near the cutoff. These results also lack statistical significance, precluding definitive conclusions about the policy's impact in this subgroup. In a notable finding, the most populous districts exhibit a positive discontinuity of approximately 24 CSR points when employing the donut hole specification. The emergence of this effect specifically under the donut design, which excludes observations immediately around the threshold, indicates that the data structure might contain year-specific heterogeneity in these densely populated regions as the effect goes away without the donut specification. Overall, however, all the terciles remain statistically insignificant.

Lastly, Figure A.7 illustrates the lagged effects of the policy intervention on CSR for districts treated in 2015, as observed in 2016. This analysis, stratified by population levels, reveals notable heterogeneity in treatment effects. The least populated group

exhibits statistically significant results, with a discontinuity estimate of 133 CSR points, equivalent to a 13.3% increase. This finding is particularly robust, although the magnitude of the effect is weakened with the donut design. The statistical significance of this result, combined with similar results observed in 2015 for districts treated in 2015, provides compelling evidence for the policy's efficacy in less populated areas.

The consistency in results across both implementation years offers valuable insights into the temporal dynamics of policy interventions like *Beti Bachao Beti Padhao*. Specifically, the evidence suggests that sustained policy exposure generates returns that exhibit only marginal diminution, pointing to the potential efficacy of persistent gender-focused interventions. This pattern of consistent effects across successive treatment cohorts contributes to the understanding of how sustained policy implementation may help maintain intervention effects with minimal degradation over time.

Moderately populated districts saw an increase of 48 CSR points. However, despite the substantial magnitude of this point estimate, it lacks statistical significance. This result suggests potential positive effects in moderately populated areas, but with considerable uncertainty. Lastly, the most populous districts also show a negative effect.

These findings provide important insights into the dynamics of the policy's impact. Firstly, the statistically significant improvement in CSR for the least populated districts underscores the potential efficacy of the intervention when per capita investment is higher. This aligns with the hypothesis that more concentrated efforts and resources per individual can yield tangible results. Additionally, the presence of significant effects in the lagged

analysis, along with immediate effects, suggests that the policy's impact may be persistent over years, with minimal degradation, if done correctly. This highlights the importance of sustained intervention and patience in evaluating policy outcomes. Lastly, the variation of effects across population terciles—strongest in the least populated and weakest in the most populated—indicates a potential inverse relationship between population of a district and policy effectiveness. This pattern may be attributed to factors such as resource dilution in more populous areas or the achievability of critical mass in campaign exposure in less dense regions. In conclusion, these results provide evidence that concentrated efforts, coupled with higher per capita investment and consistent exposure to the policy, can lead to statistically significant improvements in CSR, particularly in less populated areas. The varying magnitudes and significance levels across population groups underscore the need for nuanced, population-sensitive approaches in policy implementation and evaluation. These findings have important implications for future policy design, suggesting that tailored strategies accounting for population levels may optimize the impact of interventions aimed at addressing gender imbalances in child populations.

## **2.7 Conclusion**

This research evaluates the effectiveness of media campaigns in changing social behavior by analyzing a policy in India with the goal of improving the CSR. Using a regression discontinuity approach, I examine how the policy affected districts that received treatment in different years - 2015 and 2016. The study examines three distinct scenarios: immediate effects for districts first treated in 2015 and 2016 and delayed effects for districts treated in 2015 but observed in 2016. Since the policy's per-capita investment likely varied with district population size, I analyze its impact separately across three population groups

for these three scenarios. This approach allows me to not only assess the policy's immediate and longer-term effects but also understand how its effectiveness might depend on implementation intensity. The findings reveal nuanced patterns in how information campaigns influence deeply rooted social practices, offering insights for future policy design.

A key finding of this study is the statistically significant positive effect observed in the least populated districts (Tercile 3) immediately after exposure to treatment as well as the sustained magnitude under the staggered treatment approach. This result suggests that the policy intervention can be effective in improving CSR, particularly in areas with higher investment per-capita. The significance of this effect, especially in the one-year lagged treatment, indicates that the impact of the policy can be sustained over time and that consistent implementation could be crucial for success. Across other treatment groups and population terciles, I generally observed no statistically significant effects of the policy on CSR, except for areas with lower levels of population that experienced higher investment per capita. This lack of significant findings in two of the subgroups persisted in both immediate and lagged effect analyses. However, barring the least populated districts, the consistent positive point estimates in many of these subgroups, despite their lack of statistical significance, hint at the potential for positive impacts that may require longer-term evaluation or larger sample sizes to confirm.

In conclusion, this study provides evidence that the policy can be effective in improving CSR, particularly in less populated areas and with sustained implementation. The observed patterns of heterogeneity offer valuable insights for future research and policy refinement. Moving forward, policymakers should consider implementing strategies

to address districts with different populations differently to maximize impact as well as put emphasis on long-term implementations to allow for staggered effects.

Other researchers have found strongly positive results, however, this paper finds positive results specific only to certain area, highlighting the need for further investigation. These differences may stem from a variety of reasons. The Civil Registration System data I use captures the universe of births, while NFHS data used by Dasgupta & Sharma (2023) may have a sampling bias. The difference in results is likely also from difference in empirical strategies- while my regression discontinuity design measures the local average treatment across the treatment threshold, the triple difference strategy estimates the average effect across all treated districts.

This inconsistency in findings underscores the complexity of factors influencing child sex ratios and emphasizes the necessity for more comprehensive research in this area. Future studies should prioritize the use of more reliable and consistent data sources to ensure robust conclusions

# **AN EXAMINATION OF RACIAL AND ETHNIC DISPARITIES IN THE USE OF PROSTATE BIOPSY AND MAGNETIC RESONANCE IMAGING FOR PROSTATE CANCER SCREENING: A RETROSPECTIVE COHORT STUDY**

## **3.1 Introduction**

Prostate cancer (PCa) is the second most common cancer diagnosis in men, accounting for an estimated 27% of male cancer diagnoses in the United States in 2022 <sup>(1)</sup>. Racial disparities in PCa incidence and mortality in the United States are well documented, with Black men disproportionately impacted <sup>(2-4)</sup>. Between 2014 and 2019, the incidence of PCa in the United States was highest among Black men (172.6 per 100,000), followed by White (99.9 per 100,000), Hispanic (85.3 per 100,000), and Asian/Pacific Islander men (55.0 per 100,000) <sup>(1)</sup>. Furthermore, Black men had over two times higher mortality rates from PCa (37.9 per 100,000) compared to White (17.8 per 100,000) and Hispanic men (15.6 per 100,000), and almost four times higher mortality rates compared to Asian/Pacific Islander men (8.6 per 100,000) between 2015 and 2019 <sup>(1)</sup>. Previous research has also shown that Black men are diagnosed with PCa at a younger age than White men and are likely to be diagnosed with more aggressive disease or at later stages than men overall <sup>(3)</sup>. Traditionally, men are screened for PCa by measuring prostate-specific antigen (PSA) levels and those with abnormal PSA testing results receive a non-targeted trans-rectal ultrasound (TRUS) prostate biopsy<sup>(5)</sup>. Concerns about the cost, invasiveness, and diagnostic performance of TRUS-guided systematic prostate biopsy promoted the adoption

of alternative methods for diagnosing PCa in men with an elevated PSA, including the use of magnetic resonance imaging (MRI) and MRI-targeted prostate biopsy <sup>(6,7)</sup>. Although the American Urology Association (AUA) has recognized the importance of prostate MRI for the diagnosis of PCa<sup>(8)</sup>, recent evidence has illustrated clear differences across populations in the use of prostate MRI, with White men being referred for prostate MRI at higher rates than Black men <sup>(9,10)</sup>. Addressing these differences in access is necessary for improving clinical outcomes for patients with PCa and reducing health disparities.

While previous studies have observed clear racial and ethnic disparities in the use of prostate MRI to follow an elevated PSA level <sup>(9)</sup>, it is unclear if this trend persists when considering both MRI and TRUS-guided biopsy. In this study, I examine racial and ethnic disparities in the use of any follow-up testing (i.e., prostate biopsy or prostate MRI) to follow-up an abnormal result from a screening PSA test.

### **3.2 Method**

This study uses insurance claims data for members of large commercial and Medicare Advantage health plans from Optum's de-identified Clinformatics® Data Mart (CDM). The claims data covers all fifty states and contains lab test results for approximately 38% of the patients in the sample. The [redacted] institutional review board deemed this retrospective study of de-identified administrative claims data as not constituting human subjects research and thus not subject to review. The data analysis was performed in May 2022, and the study followed Strengthening the Reporting of Observational Studies in Epidemiology (STROBE) reporting guideline for reporting cohort studies.

The study cohort observations are restricted to all male enrollees who were continuously enrolled between the years of 2011 and 2017. Following AUA guidelines on PSA testing, the cohort was further restricted to patients who were forty years or older <sup>(11)</sup>. The sample was also restricted to enrollees undergoing a single PSA test during the study period, with no PSA test (*Current Procedural Terminology* (CPT) code: 84153) or prostate related MRI or biopsy claims in earlier or subsequent years. Following existing literature and guidelines, I define prostate related MRI as claims reporting a pelvic MRI (CPT codes: 72195, 72196, 72197) with a relevant prostate indication code (*International Classification of Diseases, Ninth Revision (ICD-9)*, and *ICD-10* codes are reported in Table B.1) and defined biopsy of the prostate as CPT codes, 55700 and G0416 <sup>(12-14)</sup>. This exclusion was intended to reduce the possibility of including patients receiving ongoing care for PCa. Finally, because urinary tract infections (UTIs) are another common cause of elevated PSA levels <sup>(15,16)</sup>, patients who underwent UTI testing (CPT codes: 87186, 87088, 87077) within 6 weeks before an elevated PSA test were removed from the sample.

Using bivariate and multivariable logistic regression analyses to estimate the association between PSA test results and subsequent diagnostic testing. The outcome variable was defined as a binary indicator of whether a patient underwent either a prostate biopsy or prostate MRI within 180 days after PSA test date. This outcome was defined both for all PSA testing dates and among the subset of PSA tests that revealed an elevated PSA level. I explore three PSA levels as thresholds for elevated PSA:

- 1.) PSA level exceeding 2.5 ng/mL, a lower threshold that is now being recognized for early detection of PCa <sup>(17)</sup>

2.) PSA level higher than 4 ng/mL is historically considered as an appropriate level to recommend a prostate biopsy <sup>(17,18)</sup>

3.) PSA level greater than 10 ng/mL, a threshold previously associated with high rates of prostate biopsy and a high rate of PCa <sup>(19)</sup>.

Multivariable logistic regressions adjusted for confounding variables including patients' age (categorized as 40-54, 55-64, 65-74, 75-84 and 85+), race and ethnicity, state of residence, the year of the PSA test, and whether the patient had Medicare Advantage or a commercial plan <sup>(20)</sup>. Race and ethnicity were self-reported by patients and recorded in the database as White, Black, Hispanic, Asian, or Unknown. Race and ethnicity were categorized as "Other" for patients where this characteristic was reported as "Unknown" or was missing in the database. All regression models estimated clustered standard errors within state of residence.

### **3.3 Results**

765,409 unique participants were identified between 2011 and 2017 meeting the study inclusion criteria, with the mean age of patients in the sample of  $59.0 \pm 11.0$  years (range 40-89). Of the complete sample, 449,750 (58.76%) were White, 71,570 (9.35%) were Black, 31,290 (4.09%) were Asian, 99,833 (13.04%) were Hispanic, and 112,966 (14.76%) were listed with a race and ethnicity of "Other." Additionally, 294,948 (38.53%) were between the ages of 40-54 years old, 233,355 (30.49%) were between the ages of 55-

64 years old, 161,747 (21.13%) between the ages of 65-74 years old, 62,151 (8.12%) between the ages of 75-84 years old, and 13,208 (1.73%) were of 85 years of age or older.

Within the sample, there were 43,711 (5.71%) patients with a PSA result above 4ng/mL. Of these, 7,399 (16.93%) underwent a prostate biopsy or prostate MRI within 180 days after the elevated PSA test results. Table B.2 reports the number of PSA tests performed, biopsy or MRI within 180 days after the PSA, PSA results > 4ng/mL, patients who underwent biopsy or MRI within 180 days after PSA tests with results 4ng/mL, and the mean days between a PSA test and biopsy or MRI, all stratified by year. Overall, the percentage of patients observed with elevated PSA results increased over time while the percentage of patients undergoing either a biopsy or MRI scan decreased. There was also an increase in the mean days between receiving elevated PSA results and undergoing a subsequent biopsy.

Table B.3 shows frequencies of the number of PSA tests performed, undergoing a biopsy or MRI within 180 days, PSA results > 4ng/mL, undergoing a biopsy or MRI within 180 days after PSA tests with results > 4ng/mL and the mean days between a PSA test and a biopsy or MRI, stratified by age for each year. In 2011, 47,018 men between ages of 40-54 years underwent a PSA test, of which 458 (0.97%) were above 4ng/mL, with 135 (29.48%) of those patients undergoing a subsequent biopsy or MRI. For men between 55-64 years, there were 36,223 PSA tests with 1,385 (3.82%) elevated results and 345 (24.91%) undergoing subsequent biopsies or MRIs. Men aged between 65-74 years underwent 17,447 PSA tests, with 1,514 (8.68%) showing elevated results and 281 (18.56%) undergoing a biopsy or MRI within 180 days. The number of tests performed for men between ages of 75-84 years old was 7,482 with 1,264 (16.89%) PSA results being

above 4ng/mL, leading to 80 (6.33%) men undergoing a biopsy or MRI. Lastly, men aged 85 or more underwent 577 PSA tests out of which 138 (23.92%) were elevated with only 5 (3.62%) men undergoing follow up biopsy.

Lastly, Table B.4 shows frequencies of the number of PSA tests performed, undergoing subsequent biopsy or MRI within 180 days, PSA tests with results > 4ng/mL, biopsy or MRI within 180 days after PSA tests with results > 4ng/mL and the mean number of days between a PSA test and the biopsy or MRI, stratified by race and ethnicity and for each year. Rates of follow-on biopsy or MRI decreased over the sample period for all races and ethnicities, Black men were observed to undergo subsequent biopsies at approximately the same rate as White men, although men with a race of Asian, Hispanic, or Other were not observed to undergo subsequent biopsies at the same rate. For example, in 2017, 821 (11.74%) White men and 202 (13.11%) Black men with elevated PSA results underwent a biopsy. The rates were lower for Asian and Hispanic men at 41 (7.87%) and 246 (9.74%) respectively.

Table B.5 reports the odds ratio of undergoing either a prostate biopsy or a prostate MRI within 180 days after an elevated PSA result. Table B.6-Table B.9 report the odds ratio of undergoing either a prostate biopsy or prostate MRI within 180 days after an elevated PSA result for ages 40-54, 55-64, 65-74, and 75 and above, respectively.

Using White patients as the reference category, Figure B.1 shows the adjusted odds-ratios from the multivariable regression models for each race and ethnicity. Compared to White men, Black men were more likely (Odds-ratio (OR): 1.16, [95% CI: 1.01, 1.32]) to undergo a subsequent prostate biopsy or MRI while all other races and ethnicities were

observed to undergo follow-up diagnostic testing at lower rates (Hispanic: 0.83 [0.70,0.97]); Asian: 0.72 [0.54,0.96]); Other: 0.85 [0.79,0.91]) following a PSA >4 ng/mL. Black patients were 22% and 10% more likely to receive a biopsy or MRI following an elevated PSA result of >2.5 ng/mL and PSA > 4.0 ng/mL respectively. However, patients of other races and ethnicities had lower levels of follow-on testing. Asian men were 20% less likely to receive a biopsy or MRI at all elevated PSA levels, and Hispanic men were 5% and 3% less likely to receive a biopsy or MRI at PSA > 2.5 ng/mL and PSA > 4.0 ng/mL respectively. There were no statistical differences found between races and ethnicities when considering the number of days between elevated PSA and subsequent prostate biopsy.

Figure B.2 displays the adjusted odds-ratios for regression analyses for each age group and race and ethnicity, using White patients as the reference category. Across all ethnicities, there was no statistical difference in the odds of a subsequent biopsy or MRI for patients aged 40-54 years. However, Black men were significantly more likely to receive a follow-up prostate biopsy or MRI with a PSA >2.5 ng/mL for age groups 55-64 (1.27 [1.14,1.42]), 65-74 (1.26 [1.10,1.45]), and above 75 (0.99 [0.66,1.48]). Hispanic patients aged 55-64 were less likely to receive prostate biopsy or MRI at all PSA levels (PSA>2.5: (0.92 [0.81,1.04]); PSA>4: (0.89 [0.75,1.06]); PSA>10: (0.95 [0.61,1.50]), although these trends were not statistically significant. While not statistically significant, Asian men were least likely to receive prostate biopsy or MRI in age groups 55-64 (0.82 [0.62,1.07]), 65-74 (0.77 [0.57,1.05]), and above 75 for PSA >2.5 ng/mL (0.77 [0.56,1.08]).

### 3.4 Discussion

This study examined retrospective health insurance claims data and the associated laboratory results for men above the age of 40 years who received an elevated PSA result and the subsequent care they received within 180 days of the PSA test. Compared to White patients, Black patients are observed receiving a follow-up prostate biopsy or MRI at a higher rate after an elevated PSA result, whereas Asian and Hispanic patients undergo follow-up testing at lower rates. These disparities were evident across all age groups, especially for patients between the ages of 65 - 74 years old. I observe that the rate of follow-up prostate biopsy or MRI after an elevated PSA result is consistent with the reported risk of PCa by race <sup>(21)</sup>, indicating that clinicians may change their follow-up decisions based on the known statistical variation in PCa risk by race.

Racial and ethnic disparities in PCa screening approaches are well documented in the literature and have been suggested as a potential source of disparities in PCa outcomes <sup>(22-25)</sup>. For example, even though PCa is known to impact Black men more than other racial groups, some studies have shown they are less likely to be screened and to receive treatment for PCa <sup>(13,20,25-27)</sup>. Clear racial and ethnic disparities additionally exist in the types of PCa screening received <sup>(23,25)</sup>. One study found that White men were more likely to be on active surveillance for PCa compared to Black men, who had 0.52 times lower odds of being on active surveillance compared to White men <sup>(22)</sup>. Additionally, recent studies have shown that Black men are significantly less likely to receive prostate MRI after an elevated PSA result <sup>(7,9,25,28)</sup>.

The results of this study stand in contrast with recent estimates of racial and ethnic disparities in individual types of PCa screening methods, and show that disparities in follow-up PCa screening when simultaneously considering prostate biopsy or MRI are more consistent with the underlying risk of PCa by race. In light of these new findings, concerns about racial disparities in the use MRI for PCa screening may be more complex to assess and possibly reflect differences in the way physicians integrate new technologies into their practice. Taken together, the results on PCa screening disparities suggest that physicians have been slower to switch from prostate biopsy to MRI for Black patients, which suggests the need for updated guidelines for PCa screening that account for new screening modalities, such as MRI.

Existing research has shown that national PCa screening guidelines are an effective way to influence physician behavior. In 2012, the United States Preventive Services Task Force (USPSTF) recommended against PSA screening for all men due to concerns of overdiagnosis and unnecessary treatment<sup>(29)</sup>. As a result, PSA screening dropped significantly<sup>(30)</sup>. In 2018, the USPSTF updated their guidelines, recommending that healthcare providers should engage in shared decision-making with their patients to inform them of the potential risks and benefits of screening<sup>(31)</sup>. The age stratified results (Figure B.2 and Table B.3) both demonstrate that follow-up PCa testing was lower for men above the age of 75. This lack of follow-up care for older men may be explained by the recent recommendation from USPSTF that patients over 75 years of age not receive screening for PCa <sup>(34)</sup>. Clear guidelines regarding the use of MRI and other novel PCa screening tools may help to reduce racial and ethnic disparities in the use of these new modalities, and may promote more consistent and standardized care.

One of the biggest limitations of this study is that all of the data were derived from a single source, which may limit the generalizability of these results to other insured populations. However, this is partially mitigated by the fact that this source contains data from thousands of different commercial and Medicare Advantage plans, covers a broad geographic area, and represents almost 15% of the U.S. population. There might also be missing observations due to deaths, which may cause these results to be biased. Another limitation of the data is that it does not contain information on the physician or other patient characteristics such as medical training, employment history, patients' general health, and family history. These additional factors are likely to play an important role in the choice of PCa screening, and should be investigated in future research. Also, given the use of claims data, it is not possible to identify whether the prostate biopsies comprised only systematic cores, only MRI-targeted cores, or both systematic and targeted cores. Lastly, the results describe associations and cannot be interpreted as causal, and more rigorous analyses are necessary to better estimate these trends.

### **3.5 Conclusion**

This study shows that physicians use the reported statistical incidence of prostate cancer by race and ethnicity to make decisions about follow-up testing for patients with elevated PSA results. Specifically, these results show that men with an elevated PSA result are most likely to receive a follow-up prostate biopsy or prostate MRI if they are Black, followed by White, Hispanic, and Asian. These results demonstrate the importance of

publishing statistical data on disease incidence by race and ethnicity for informing physicians' decision-making.

# COMPARISON OF LUNG CANCER SCREENING ELIGIBILITY AND USE BETWEEN COMMERCIAL MEDICARE, AND MEDICARE ADVANTAGE ENROLLEES

## 4.1 Introduction

Lung cancer remains the most preventable and leading cause of cancer mortality in the United States – more than prostate, breast, and colorectal cancers combined.<sup>1,2</sup> The National Cancer Institute estimates that in 2022, lung cancer will account for 12.3% of all new cancer cases, but 21.4% of cancer deaths overall.<sup>2</sup> Although the current five-year survival rate is only 22.9%, lung cancer prognoses greatly depend on the stage at diagnosis.<sup>2</sup> In contrast to survival rates for lung cancer overall, patients diagnosed with Stage 1 lung cancers have a 61.2% five-year survival rate. Conversely, the 55% of patients diagnosed with Stage 3 (“distant”) lung cancer that was not detected until after it had metastasized face a much lower five-year survival rate of 7.0%.<sup>2</sup>

The landmark National Lung Screening Trial (NLST) found that participants randomized to the group undergoing lung cancer screening using low-dose computed tomography (LDCT) had 20% fewer cancer deaths relative to a control group that was offered chest x-ray, demonstrating the advantage of more sensitive imaging technology for detecting lung cancers earlier in the disease progression.<sup>3,4</sup> Because of the substantial impact of LDCT screening, the United States Preventive Services Task Force (USPSTF) initially recommended adults aged 55 to 77 years with a 30 pack-year smoking history and currently smoke or quit within the past 15 years receive LDCT screening.<sup>5</sup> However, in

2021, based largely on new evidence from the Nederlands-Leuvens Longkanker Screenings Onderzoek (NELSON) trial,<sup>6</sup> the USPSTF expanded its recommended eligibility criteria to begin screening at age 50 years and for adults who have a 20 pack-year smoking history.<sup>7, 8</sup>

Under the Affordable Care Act, most health insurance carriers are required to cover screening with no cost sharing for patients who meet USPSTF eligibility requirements.<sup>9, 10</sup> Despite the removal of these financial barriers to lung cancer screening, concerns exist that many fewer people are screened than currently recommended.<sup>11-13</sup> Continued barriers to screening include the clinical challenge of identifying adults eligible for screening based on history of tobacco use, low-rates of referral from primary care, lack of health insurance among eligible patients under age 65, lack of access to LDCT facilities and concerns about substantial cost sharing (which can vary greatly by payer) associated with recommended recalls for a positive test.<sup>14-20</sup> These concerns are exacerbated by recent research indicating the NLST under-represented Black patients, a population presently experiencing the highest lung cancer morbidity and mortality.<sup>21</sup>

In this study multiple data sources are used to estimate and compare LDCT screening rates between populations of insured patients by different payer types, specifically, commercial plans, Medicare fee-for-service (i.e. Part A & B), and Medicare Advantage, and for a number of enrollee demographic and geographic characteristics. Together this data can inform practitioners and policy makers on how to best target efforts to increase lung cancer screening in vulnerable populations.

## 4.2 Methods

This retrospective study of de-identified 2017 medical claims data was deemed exempt from review by [redacted]'s institutional review board based on being an analysis of deidentified data. The study independently examines two large medical claims datasets. The first is the 2017 Optum's de-identified Clinformatics® Data Mart (CDM), which contains all administrative medical claims associated with over 40 million members of large commercial and Medicare Advantage health plans. The second is the 2017 Centers for Medicare & Medicaid Service's (CMS) 5% Research Identifiable Files (RIF) which contain all final action Medicare fee-for-service (FFS) claims (i.e. Parts A and B) associated with a 5% national sample of Medicare enrollees. Both data sets contained their beneficiaries' enrollment period, age, sex, ZIP code of residence, and the Healthcare Common Procedure Coding System (HCPCS) codes reported on each claim. The CDM included whether the enrollee was in a commercial or Medicare Advantage plan. The 5% RIF data also included beneficiary race.

Separately for the CDM and 5% RIF, I identified all enrollees that were aged 55-77 years on January 1, 2017. Of these, I identified enrollees who underwent LDCT (HCPCS: G0297) within the calendar year. Because I evaluate 2017 claims data, I examine screening in adults aged 55-77 consistent with the 2013 USPSTF recommendations. The total number of enrollees aged 55-77 and the total number of enrollees aged 55-77 that underwent LDCT by ZIP code separately for the CDM and 5% RIF data are then aggregated. The ZIP code level results were then mapped and aggregated to the county level using population density weights from the U.S. Housing and Urban Development crosswalk files.<sup>22</sup>

A common approach for estimating the number eligible for LDCT in administrative datasets is to multiply smoking rates derived from the Centers for Disease Control's (CDC) Behavioral Risk Factor Surveillance System (BRFSS) to the number of enrollees aged 55-77.<sup>1,23-24</sup> Because BRFSS data stopped reporting county identifiers for respondents in 2013, the existing literature has focused on state level analyses. However, the University of Wisconsin's County Health Rankings (CHR) report county smoking rates that are directly provided to them by the CDC.<sup>25</sup> These smoking rates are produced using the confidential BRFSS data and are then adjusted by numerous county level demographics using American Community Survey (ACS) data including age, gender, and ethnicity.<sup>25-27</sup> I apply these county level adjusted smoking rates to the total number of enrollees aged 55-77 in each county separately to the 5% RIF and CDM data to estimate the number of enrollees eligible for LDCT for each payer. After estimating the number of CDM and 5% RIF enrollees eligible in each county for screening, I calculate the county level LDCT screening rate for each sample by dividing the number of enrollees receiving LDCT by the estimated number of enrollees eligible for lung cancer screening.

To examine variation in payer type and enrollee characteristics on LDCT screening rates, I aggregate county level estimates of LDCT eligible enrollees and enrollees undergoing LDCT by commercial (CDM), Medicare Advantage (CDM), and Medicare FFS (5% RIF) payer and then stratified by (1) sex, (2) age group (55-64, 65-74, 75-77), (3) census region of residence (Northeast, South, Midwest, West), (4) whether county of residence is rural or urban, and for the 5% RIF data (5) race/ethnicity (non-Hispanic White, non-Hispanic Black, Other). For both screened and eligible populations, chi-square tests were performed to test for statistically significant differences in enrollee characteristics

between Medicare FFS and Medicare Advantage populations and between Medicare Advantage and commercially covered populations. I then calculated the LDCT screening rate by enrollee characteristic by payer. Chi-square tests were performed to test for differences in screening rates by enrollee characteristic and payer.

The overall screening rate for each payer sample was also estimated to facilitate comparisons with previous studies.<sup>23-24,28</sup> I also used chi-square tests to test for statistical differences in the LDCT screening rate between the following samples: (1) Medicare Advantage vs. commercial (2) Medicare Advantage vs. Medicare FFS, (3) (Medicare FFS + Medicare Advantage) vs. commercial, (4) (Medicare Advantage + commercial) vs. Medicare FFS (i.e. CDM sample vs 5% RIF) and (5) Medicare FFS vs. commercial.

Finally, because the USPSTF guidelines recommend screening for individuals with 30+ pack-years of smoking and the CHR reported smoking rates include everyone 18+ years of age responding as a current smoker in the BRFSS survey, I perform a robustness test by re-running the analysis using alternative smoking rates derived from the 2018 CDC State Tobacco Tracking and Evaluation System (TUS-CPS) using the method employed by Taylor *et. al.*<sup>24</sup> which can be found in the online supplemental appendix.

Initial data management and analysis were performed using SAS (version 9.4, SAS Institute, Cary, North Carolina), and subsequent analysis was performed using Excel (Microsoft, Redmond, Washington), and Stata (version 16, StataCorp, College Station, Texas). All statistical tests of significance were evaluated as two-sided tests with  $\alpha = 0.01$ .

### 4.3 Results

The CDM sample contained 2,204,652 commercial and 3,230,763 Medicare Advantage enrollees aged 55-77 in 2017. The 5% RIF sample contained 1,441,328 Medicare FFS enrollees. The samples covered 96% (3,074 of 3,193) of county equivalents in the 50 states plus District of Columbia.

#### 4.3.1 *Characteristics of Eligible Enrollees*

Of the 6,876,743 combined enrollees, 1,077,142 (15.7%) were estimated to be eligible for LDCT screening (Table C.1). Across all insurance types, a higher proportion of enrollees eligible for screening resided in the South than any other region (41.4%-47.2%) or were living in an urban rather than a rural location (97.3%-98.1%). For both Medicare FFS and Medicare Advantage, more females (52.1% and 56.6%, respectively) were eligible than males, and more enrollees aged 65 to 74 (74.7% and 71.6%) than those aged 55-64 or 75-77. In contrast, amongst commercial enrollees, the majority of the eligible population were men (51.1%) and aged 55-64 (83.3%). All distributional comparisons between both i) Medicare FFS and Medicare Advantage and ii) Medicare Advantage vs commercial enrollees were statistically significant ( $P < 0.001$  for all categories).

#### 4.3.2 *Characteristics of Screened Enrollees*

Across all insurance types in the claims data, a higher proportion of screened patients were male (50.2%-56.8%), residing in the South (37.1%-40.5), and living in an

urban location (98.1%-98.6%) than their comparison groups (Table C.2). For both Medicare FFS and Medicare Advantage, the majority of their screened populations were aged 65 to 74 (72.1% and 71.5%, respectively), whereas most of the commercial screened population were aged 55 to 64 (82.6%). Medicare FFS and Medicare Advantage enrollees showed similar distributions of screening utilization when stratified by gender ( $P = 0.638$ ) and age ( $P=0.015$ ), however, they differed significantly by region, and rural-urban classification ( $P < 0.001$  for all categories). The distributions of screening utilization for commercial enrollees differed significantly based on Medicare Advantage coverage when stratified by gender ( $P < 0.001$ ), age ( $P < 0.001$ ), and region ( $P < 0.001$ ), and rural-urban classification ( $P < 0.001$ ).

#### 4.3.3 *Sample Screening Rates*

For both Medicare FFS and Medicare Advantage, screening rates were highest for enrollees aged 55 to 64 (5.0% and 6.8%, respectively) and for those living in an urban environment (3.4% and 4.6%) (Table C.3). In contrast, of the commercial enrollees, those aged 65 to 74 (1.9%) and who live in a rural environment (1.9%) had the highest estimated screening rates. Across all payers, LDCT screening rates were higher for males (Medicare FFS: 3.6%; Medicare Advantage: 5.3%; commercial: 2.0%) and enrollees residing in the Northeast (Medicare FFS: 4.7%; Medicare Advantage: 6.5%; commercial: 2.9%). All intra-category comparisons between both Medicare FFS vs Medicare Advantage ( $P < 0.001$  for all comparisons) and Medicare Advantage vs commercial ( $P < 0.001$  for all comparisons) enrollees were statistically significant at  $\alpha = 0.01$ .

Estimated sample screening rates for the combined populations of Medicare FFS and Medicare Advantage enrollees aged 55-77 (4.19%) (Table C.4) were larger than those for commercial enrollees (1.75%,  $P < 0.001$ ). Estimated rates for the combined CDM populations of Medicare Advantage and commercial enrollees (3.43%) were not significantly different than for Medicare FFS enrollees (3.37%,  $P < 0.159$ ). Estimated rates for Medicare Advantage enrollees (4.56%) were larger than for Medicare FFS enrollees (3.37%,  $P < 0.001$ ).

The robustness test using an alternative method for estimating the number of eligible LDCT enrollees (Tables C.5 - Table C.6), produced higher estimated smoking rates (Table C.7) than produced in the primary analysis (Table C.3). The relationship in smoking rates between payers (Medicare FFS: 4.4%; Medicare Advantage: 5.4%; commercial: 1.4%) (Table C.8) were similar to those in the primary analysis above.

#### **4.4 Discussion & Conclusion**

Examining Medicare and commercial claims data, I estimate LDCT utilization rates for commercial, Medicare FFS, and Medicare Advantage insured samples. The overall 2017 screening rates for Medicare FFS (3.37%) and Medicare Advantage (4.56) enrollees is close to the 3.4-4.0% found in a recent study using 2018 American College of Radiology lung cancer screening registry (ACR-LCSR) data.<sup>28</sup> The estimated rates for commercial and Medicare FFS enrollees in this study are lower than previous estimates. For example, Okereke et al, who also used 2017 CDM data, estimated the LDCT rate as 4.6%, while I

estimate it to be around 3.43%.<sup>23</sup> Similarly, I estimate the Medicare FFS rate as 3.37% vs Tailor *et. al.*'s 4.1% which used a 100% sample of 2016 Medicare data.<sup>24</sup> The slight differences may be attributed to these studies' including additional Medicare plans and application of smoking rates at the state level rather than the more granular county level approach used in this study. Applying Tailor *et. al.*'s method to this Medicare FFS sample produced a higher rate of 4.4%, though it should be noted that the TUS-CPS data only contains county level data for the 270 largest urban areas which would bias this study's estimate. The substantially lower estimated commercial LDCT rate compared to the two Medicare samples is largely a function of the inherent systematic difference between these comparison groups, since the Medicare groups skew significantly older overall.

Consistent with findings from breast cancer screening, eligible Medicare Advantage enrollees underwent LDCT at a higher rate than Medicare FFS enrollees.<sup>29</sup> Eligible commercially insured enrollees participated in LDCT at substantially lower rates than either Medicare or Medicare Advantage enrollees. Since patient education and physician engagement influence the use of screening,<sup>30, 31</sup> which has been observed with the historical rise in screening rates for cancers for the other cancers in which screening is well established, I expect the uptake of lung cancer screening also will climb among eligible individuals and health insurance as patient and provider awareness and engagement increase.<sup>32, 33</sup>

Additionally, I find substantially lower screening rates among non-White Medicare FFS beneficiaries, the only sample where race/ethnicity data was available. The results indicate that among the LDCT-eligible Medicare population, non-Hispanic Black and Other races utilized LDCT at a frequency disproportionately lower than non-Hispanic

White beneficiaries. A primary cause for non-Hispanic Black enrollees to be unscreened for lung cancer is lack of awareness of lung cancer screening programs,<sup>34</sup> and the results thus highlight another opportunity for educating non-White patients and better engaging their providers. Additionally, despite having a higher prevalence of smoking behavior and incidence of lung cancer, non-Hispanic Black enrollees are reported to have lower intensity of smoking, rendering the group less likely to be eligible for lung cancer screenings under the previous 2013 USPSTF criteria.<sup>35-37</sup> The recent expansion of LDCT eligibility to include adults ages 50-80, and individuals with 20 to 29 pack years of smoking history improves LDCT coverage for high-risk non-Hispanic Black individuals who ever smoked and potentially increase their access to and utilization of screening.<sup>38-40</sup>

The results show that LDCT rates varied by geography in two important ways. First, regardless of payer, enrollees in the Northeast region undergo LDCT at much higher rates compared to the rest of the country. As others have suggested, this may be attributed to the availability of American College of Radiology accredited lung cancer screening facilities, which are more concentrated in the Northeast.<sup>1, 24, 42</sup> Furthermore, rural areas have lower LDCT rates than urban areas.<sup>18</sup> Despite having larger eligible populations due to higher smoking rates, enrollees residing in rural areas face greater barriers to access than urban enrollees because of factors such as lack of referral from a health care provider, inadequate transportation, greater average distances to the closest LCS facility, and lower rates of insurance.<sup>1,12,14,20,43,44</sup> **Error! Bookmark not defined.** Further research is needed to examine the socioeconomic determinants for lung cancer screening and explore strategies to expand access to LDCT screening facilities.

Among this study's limitations, the results are not likely to be generalizable to Medicaid or uninsured populations. The commercial estimates may not be generalizable to commercial carriers not represented in the sample. However, because the Affordable Care Act mandates coverage with no cost sharing for LCS due to its USPSTF "B" rating, other commercial plans financial mechanisms should not influence their enrollees' decision to screen. Moreover, the large number of distinct plans in the sample – and large sample size overall – at least partially mitigate this concern. Like previous studies, these estimates for lung cancer screening eligibility ultimately rely on CDC's BRFSS self-reported smoking data to estimate eligibility which do not capture the duration of smoking history and may bias estimates of the eligible population. As the CHR reported adjusted BRFSS data is at the county level, the smoking rates may be higher than in the commercially and Medicare insured study populations due to the higher smoking rates among uninsured and Medicaid populations included in the BRFSS sample. Finally, all claims data are limited to their insurance coverage patterns which could bias regional estimates. Nonetheless, the results show that the overall estimates are consistent with those of insured populations. Despite these limitations, this data is important to healthcare policymakers and providers given lack of inclusion of LCS questions in the core BRFSS questionnaire until 2022, the infrequent measurement of screening in the NHIS, and the recent CMS decision to no longer require imaging facilities to report their LCS data.

In conclusion, this study of LDCT utilization among commercial, Medicare Advantage, and Medicare FFS populations reveals that the utilization rate of LDCT was low in 2017, with only approximately 1.75%-4.56% of eligible individuals receiving LCS. Although screening rates were low across all subgroups examined, there appear to be

substantial disparities in LDCT usage among rural non-White populations.<sup>45</sup> Although LCS rates are increasing, albeit slowly,<sup>28, 46</sup> now is the time to identify disparities and underutilization across states and within the population groups eligible for screening. Efforts specifically targeting historically vulnerable populations could present opportunities for outsized gains to public health.

## APPENDIX A

Table A. 1: Descriptive Statistics of Dataset

The data comes from the vital statistics dataset, managed by the Civil Registration System, which records comprehensive birth related information at the district level. The level of reporting rose consistently from 81% in 2001 to 86% in 2016 nationally.

	<b>Control</b>	<b>Treated - 2015</b>	<b>Treated - 2016</b>
<b>Avg Births – 2011</b>	<b>29594</b>	<b>35113</b>	<b>32080</b>
<b>Avg Male Births - 2011</b>	<b>15452</b>	<b>18740</b>	<b>17135</b>
Avg Male Births- Rural	6910	6489	6420
Avg Male Births- Urban	8542	12251	10715
<b>Avg Female Births - 2011</b>	<b>14142</b>	<b>16373</b>	<b>14944</b>
Avg Female Births - Rural	6320	5659	5607
Avg Female Births - Urban	7821	10713	9337
<b>Avg CSR - 2011</b>	944	859	872
<b>Observations - Total</b>	3202	651	403
<b>Number of Individual Districts - 2011</b>	343	79	50

Table A. 2: CSR by District- 2001 and 2011

The table provides a comparison between the child sex ratios observed in different states in the two most recent census. While the child sex ratio has improved for some states, the overall trend has been downwards, with the national average falling from 927 to 919

State/UTs	Child Sex Ratio	
	Census-2001	Census-2011
<b>INDIA</b>	<b>927</b>	<b>919</b>
Jammu & Kashmir	941	862
Himachal Pradesh	896	909
Punjab	798	846
Chandigarh	845	880
Uttarakhand	908	890
Haryana	819	834
NCT of Delhi	868	871
Rajasthan	909	888
Uttar Pradesh	916	902
Bihar	942	935
Sikkim	963	957
Arunachal Pradesh	964	972
Nagaland	964	943
Manipur	957	936
Mizoram	964	970
Tripura	966	957
Meghalaya	973	970
Assam	965	962
West Bengal	960	956
Jharkhand	965	948
Odisha	953	941
Chhattisgarh	975	969
Madhya Pradesh	932	918
Gujarat	883	890
Daman & Diu	926	904
Dadra & Nagar Haveli	979	926
Maharashtra	913	894
Andhra Pradesh	961	939
Karnataka	946	948
Goa	938	942
Lakshadweep	959	911
Kerala	960	964
Tamil Nadu	942	943
Puducherry	967	967
A. & N. Islands	957	968

Table A. 3: Discontinuity Estimates for districts treated in 2015 and 2016 along with the CER optimal bandwidth

	<b>Treated - 2015</b>		<b>Treated - 2016</b>	
	Cutoff - 872	Donut	Cutoff - 892	Donut
<b>CSR - 2015</b>	-24.35	-35.27		
	(33.48)	(83.20)		
<b>Bandwidth</b>	21.17	36.85		
<b>CSR - 2016</b>	7.22	-42.29	-26.89	13.98
	(31.18)	(96.11)	(39.27)	(49.63)
<b>Bandwidth</b>	23.48	31.5	15.96	18.66

Table A. 4: Discontinuity Estimates for districts treated in 2015 and 2016 along with the CER optimal bandwidth, stratified by population level

<b>Treated - 2015</b>						
	<b>Tercile 1: Most Populated</b>		<b>Tercile 2: Mid-Populated</b>		<b>Tercile 3: Least Populated</b>	
	Cutoff - 872	Donut	Cutoff - 872	Donut	Cutoff - 872	Donut
<b>CSR - 2015</b>	-75.54	-8.49	58.14	-16.55	134.46**	-28.33
	(31.21)	(93.40)	(102.51)	(149.9)	(56.80)	(137.30)
<b>Bandwidth</b>	12.3	17.23	16.47	15.34	21.9	30
<b>CSR - 2016</b>	-65.48	-77.01	48.75	-63.56	133.08**	-98.19
	(37.58)	(121.96)	(56.19)	(39.09)	(60.66)	(151.36)
<b>Bandwidth</b>	12.98	19.37	14.16	46.81	23.51	30.58
<b>Treated - 2016</b>						
	<b>Tercile 1: Most Populated</b>		<b>Tercile 2: Mid-Populated</b>		<b>Tercile 3: Least Populated</b>	
	Cutoff - 892	Donut	Cutoff - 892	Donut	Cutoff - 892	Donut
<b>CSR - 2016</b>	-12.71	23.81	21.06	-139.22	96.55	114.28
	(75.37)	(74.78)	(41.02)	(88.73)	(95.94)	(86.11)
<b>Bandwidth</b>	14.62	39.58	14.14	13.11	14.48	11.88

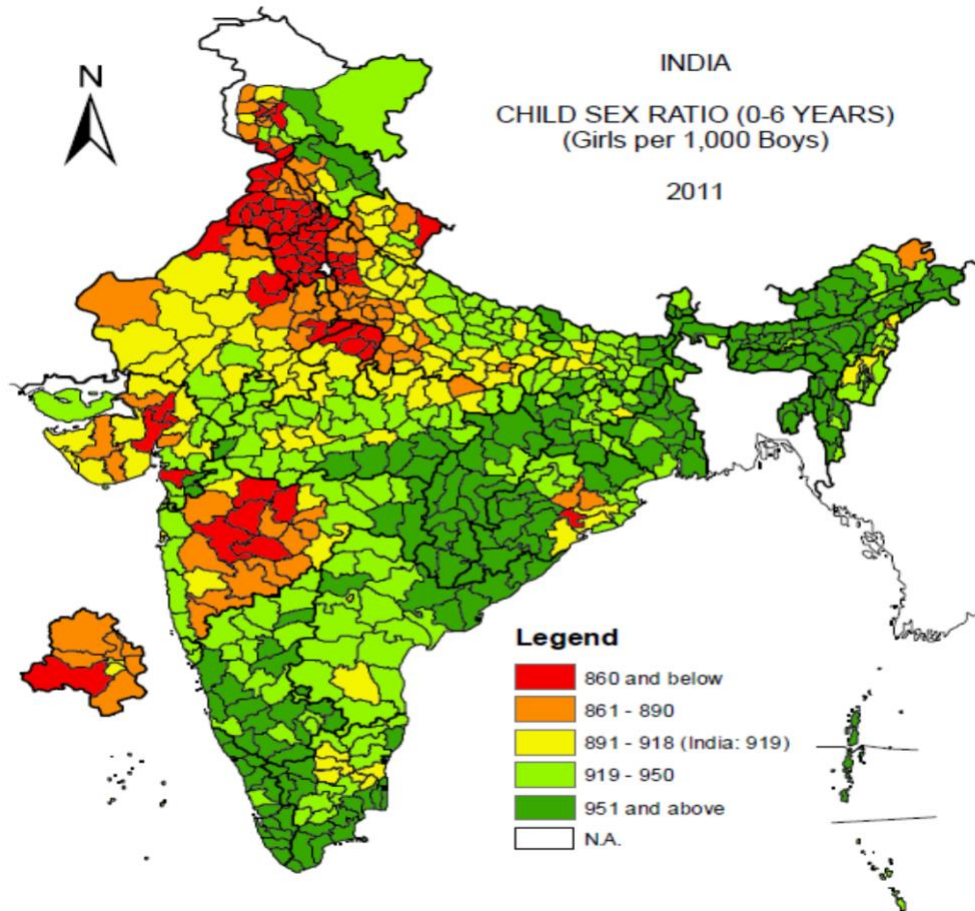


Figure A. 1: CSR by District - 2011

The image shows the Child Sex Ratio in every district in India according to the 2011 census. It depicts a clear son preference and skewed child sex ratios across the entire country, especially in the North-West regions.

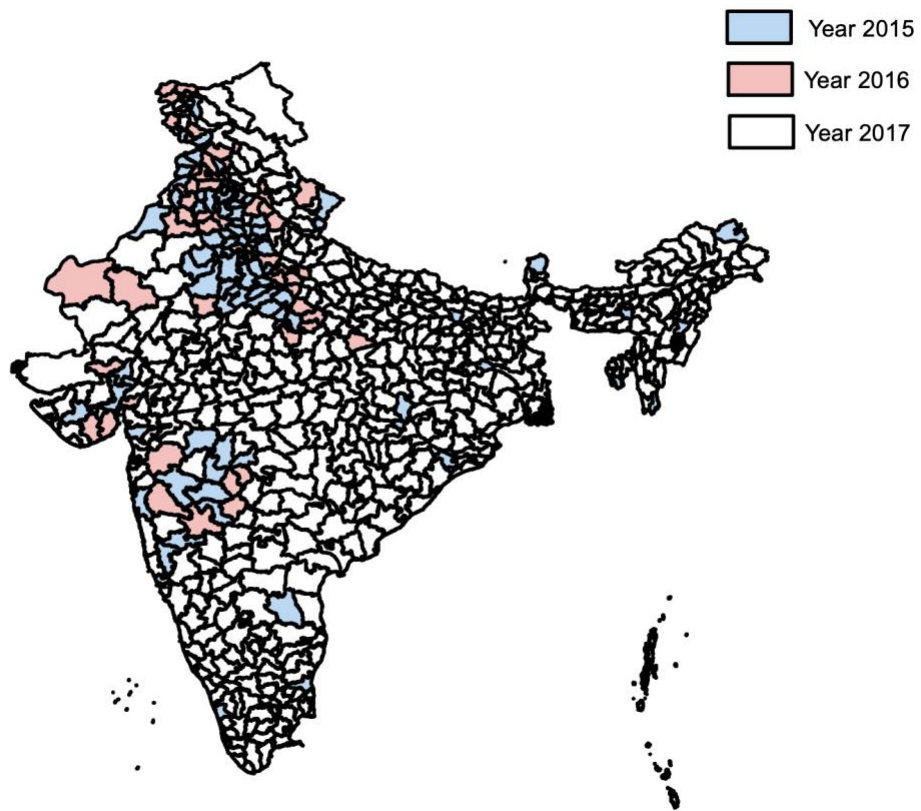


Figure A. 2: Policy rollout by Year

The Figure visualizes the staggered rollout of the policy where a hundred districts were treated in the year 2015, sixty-one additional districts were treated in 2016 and the entire country was considered treated in 2017. These districts were chosen based on the CSR observed in the 2011 census

Vital Statistics  
Treated in 2015 & 2016

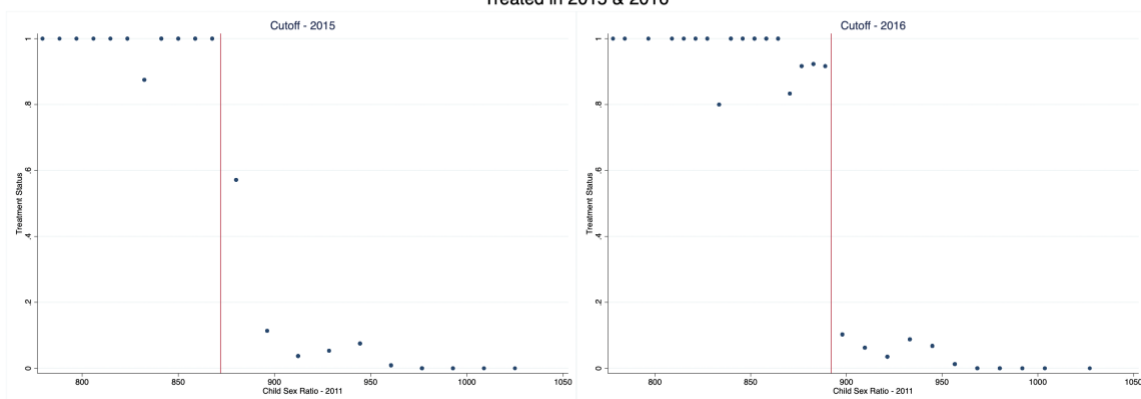


Figure A. 3: Treatment status based determined by the CSR from the 2011 census

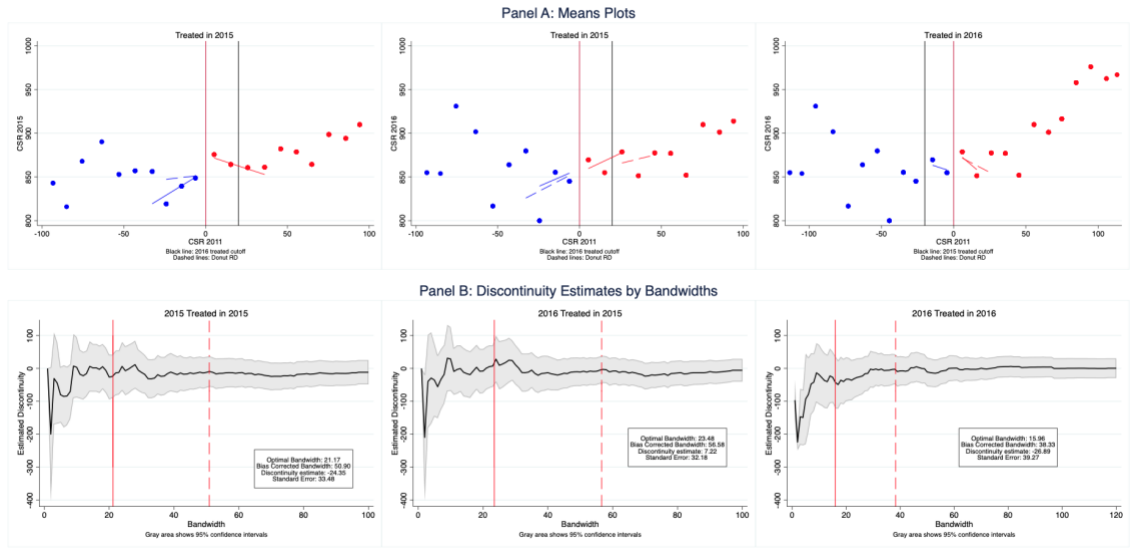


Figure A. 4: Effects of BBBP on CSR for districts treated in 2015 and 2016

The figure presents results using the Vital Statistics Data. Panel A shows binned means with each bin consisting of 10 CSR points with linear regressions fitted on either side of the cutoff and the dashed lines showing the fit for the donut specification. Panel B shows the point estimation for the regular RD specification using uniform kernels, weighted by total number of births, with emphasis on the CER optimal bandwidth, as well as the 95% confidence intervals. The text box shows the optimal bandwidth and the bias corrected optimal bandwidth as per Calonico et.al.(2020) along with the point estimate and the standard error. The significance levels for point estimates are denoted using asterisks (\*) following standard conventions: \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ .

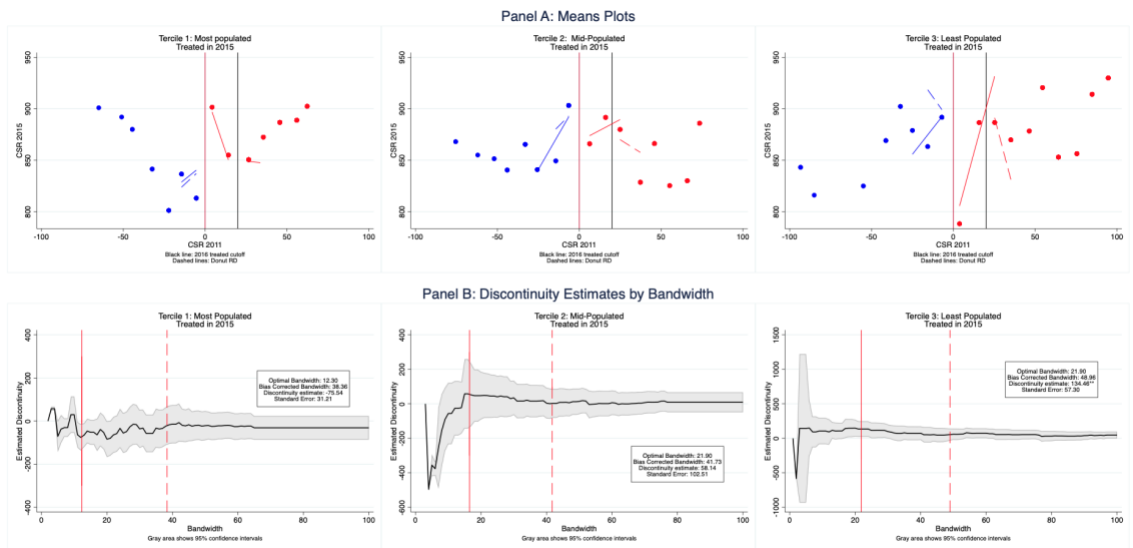


Figure A. 5: Impact of BBBP on CSR in 2015– By Population Size

The figures show the impact of the policy on CSR in 2015 for three population groups that were treated in 2015. Panel A shows binned means with each bin consisting of 10 CSR points with linear regressions fitted on either side of the cutoff and the dashed lines showing the fit for the donut specification. Panel B shows the point estimation for the regular RD specification using uniform kernels, weighted by total number of births, with emphasis on the CER optimal bandwidth, as well as the 95% confidence intervals. The textbox shows the optimal bandwidth and the bias corrected optimal bandwidth as per Calonico et.al.(2020) along with the point estimate and the standard error. The significance levels for point estimates are denoted using asterisks (\*) following standard conventions: \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ .

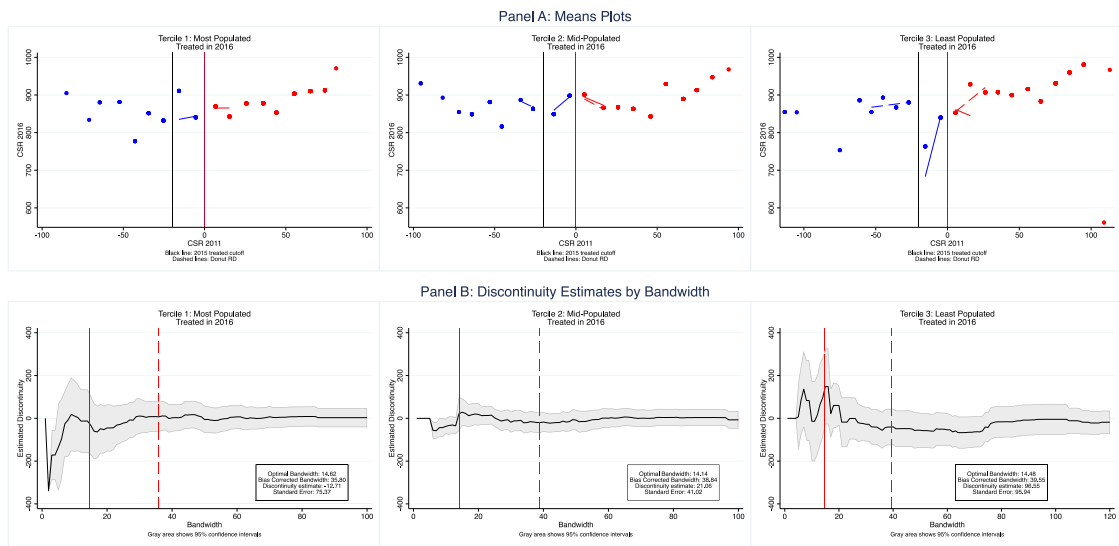


Figure A. 6: Impact of BBBP on CSR in 2016 – By Population Size

The figures show the impact of the policy on CSR in 2016 for three population groups that were treated in 2016. Panel A shows binned means with each bin consisting of 10 CSR points with linear regressions fitted on either side of the cutoff and the dashed lines showing the fit for the donut specification. Panel B shows the point estimation for the regular RD specification using uniform kernels, weighted by total number of births, with emphasis on the CER optimal bandwidth, as well as the 95% confidence intervals. The textbox shows the optimal bandwidth and the bias corrected optimal bandwidth as per Calonico et.al.(2020) along with the point estimate and the standard error. The significance levels for point estimates are denoted using asterisks (\*) following standard conventions: \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ .

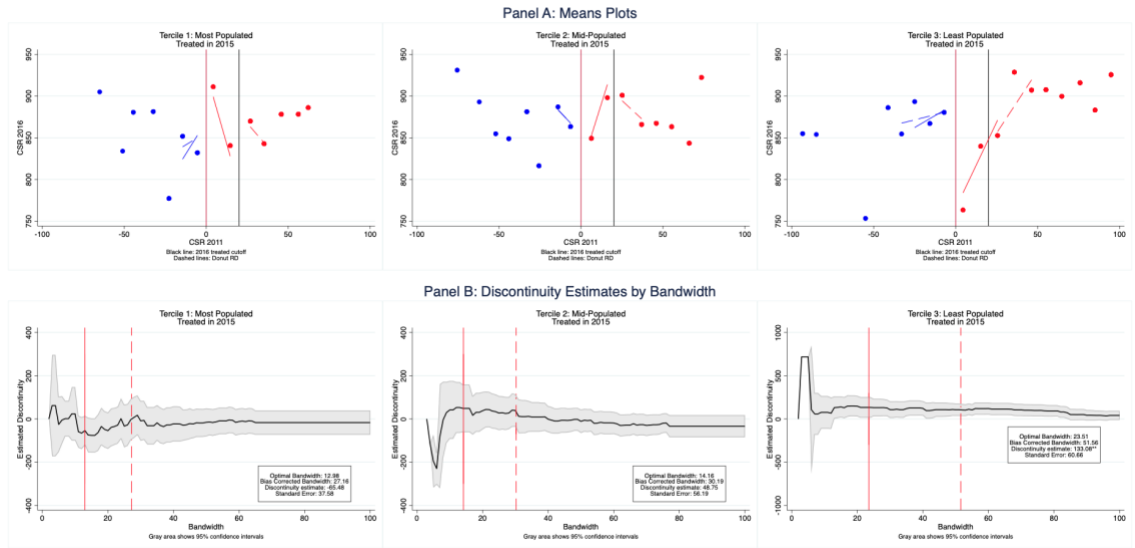


Figure A. 7: Impact of BBBP on CSR in 2016 for districts treated in 2015 – By Population Size

The figures show the impact of the policy on CSR in 2016 for three population groups that were treated in 2015, a lagged effect of the policy. Panel A shows binned means with each bin consisting of 10 CSR points with linear regressions fitted on either side of the cutoff and the dashed lines showing the fit for the donut specification. Panel B shows the point estimation for the regular RD specification using uniform kernels, weighted by total number of births, with emphasis on the CER optimal bandwidth, as well as the 95% confidence intervals. The textbox shows the optimal bandwidth and the bias corrected optimal bandwidth as per Calonico et.al.(2020) along with the point estimate and the standard error. The significance levels for point estimates are denoted using asterisks (\*) following standard conventions: \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ .

## Density Test by Treatment Year

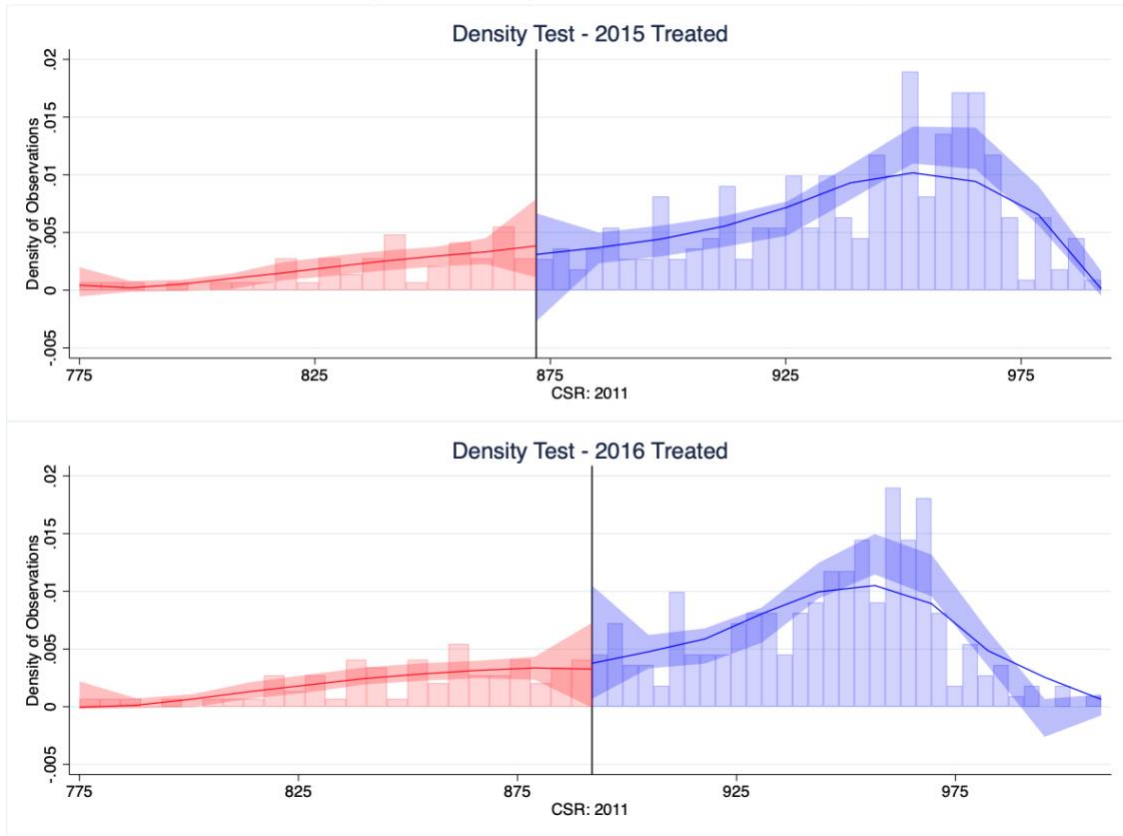


Figure A. 8: Density Test by Year of Treatment

The figure shows the distribution of observations across the cutoff for the years of treatment. The T-stat is -0.88 for 2015 and 0.54 for 2016 with statistically insignificant p-value for both years indicating towards no significant evidence of sorting or manipulation across the cutoff.

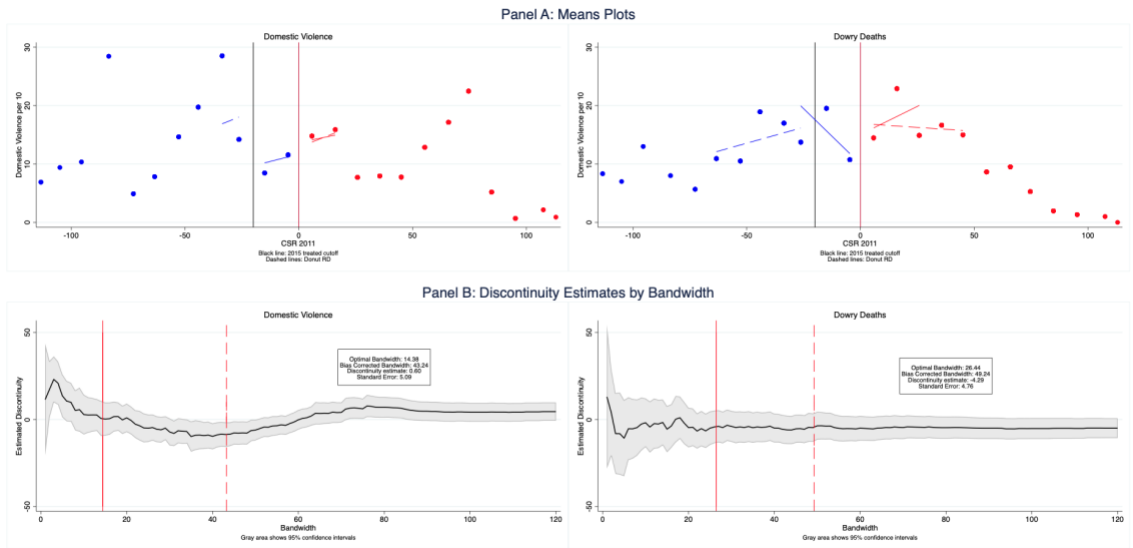


Figure A. 9: Crimes Against Women in the Household - 2011

The figure shows trends in crimes against women that happen within the household in 2011. Marital rape is considered legal in India and hence, cannot be teased out of the total rape and assault statistics and so, has not been taken into account. Panel A provides binned estimates of instances of domestic violence and dowry deaths while Panel B provides the discontinuity estimate for various bandwidths. Overall, no significant difference is observed between the two groups.

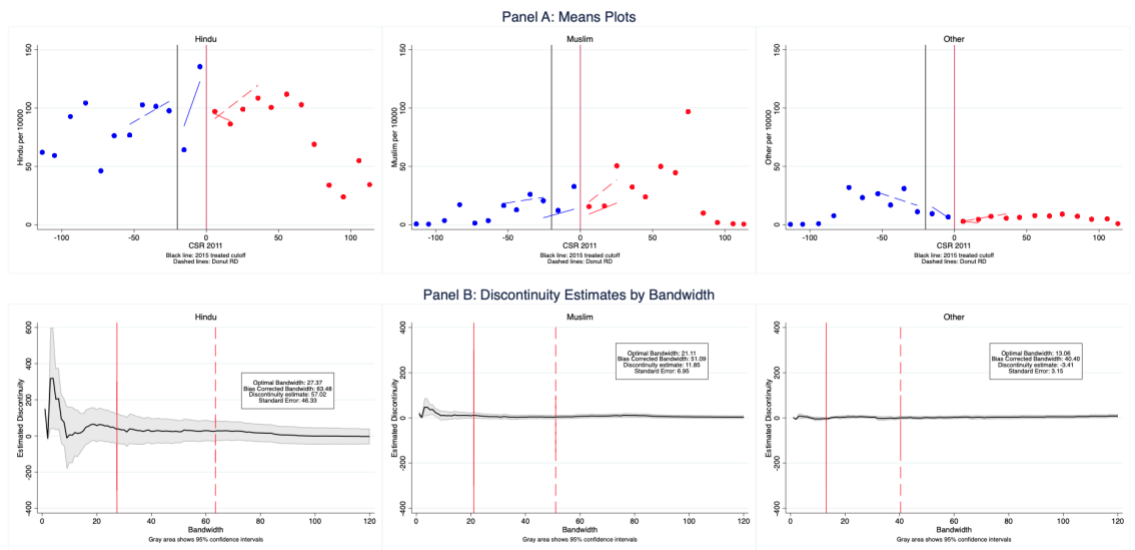


Figure A. 10: Religion by Treatment Year

The figure depicts the pre-treatment distribution of religions in 2011 across the treatment cutoffs for different years. Hindus made up almost 80% of the population in 2011 and Muslims made up an additional 14.2%. Panel A shows binned means for each religious group per 1000 individuals while Panel B depicts the discontinuity estimates for various bandwidths.

## Births in 2011 (Per 1000)

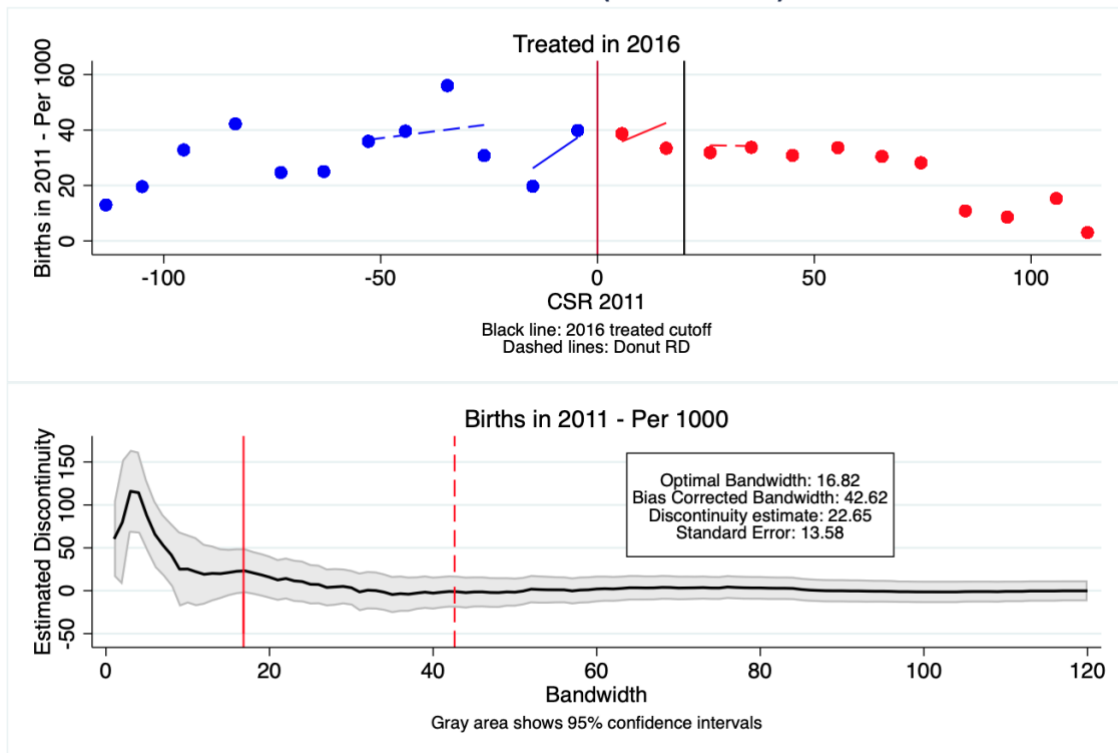


Figure A. 11: Birth Rate for 2016

The figure depicts trends in Birth Rates for year 2011 across the treatment threshold for the year of 2016. There are no significant differences observed in the number of births below and above the threshold.

## APPENDIX B

Table B. 1: International Classification of Diseases, Ninth Revision (ICD-9), and Tenth Revision (ICD-10) Indications for Prostate Diagnoses

<b>ICD-9</b>	<b>ICD-10</b>
185; 60000; 79093; 2334; 60010; 6011; V1046; 60001; 6029; 60020; 60090; 6028; 2222; 2365; 6003; 60091; 60011; 6023; 6010; 6020; V1642; 6012; 6021; 6019	C61; N400; R972; R9720; D075; N402; N411; Z8546; N401; N429; D4289; D291; D400; D4283; N403; N423; N410; N420; Z8042; N412; N421; N419

Table B. 2: Annual Frequency of PSA Testing and Subsequent Prostate Biopsy

Year	Number of PSA Tests	Biopsy or MRI within 180d	PSA test >4	PSA test >4 and biopsy or MRI within 180d	Mean time between all PSA tests and biopsy or MRI, d
		No. (%)	No. (%)	No. (%)	
<b>2011</b>	108,747	1,189 (1.09)	4,759 (4.38)	853 (17.92)	52
<b>2012</b>	83,990	871 (1.04)	3,877 (4.62)	639 (16.48)	54
<b>2013</b>	88,483	872 (0.99)	4,490 (5.07)	674 (15.01)	53
<b>2014</b>	74,347	655 (0.88)	3,885 (5.23)	528 (13.59)	54
<b>2015</b>	94,700	935 (0.99)	5,050 (5.33)	759 (15.01)	56
<b>2016</b>	118,090	1,253 (1.06)	6,716 (5.69)	1,008 (15.01)	59
<b>2017</b>	197,052	2,299 (1.17)	14,934 (7.58)	1,936 (12.96)	56

Table B. 3: Annual Frequency of PSA Testing and Subsequent Prostate Biopsy, Stratified by Age

Year	Age, y	Number of PSA Tests	Biopsy or MRI within 180d	PSA test >4	PSA test >4 and biopsy or MRI within 180d	Mean time between all PSA tests and biopsy or MRI, d
			No. (%)	No. (%)	No. (%)	
<b>2011</b>	40-54	47,018	224 (0.48)	458 (0.97)	135 (29.48)	47
	55-64	36,223	487 (1.34)	1,385 (3.82)	345 (24.91)	56
	65-74	17,447	357 (2.05)	1,514 (8.68)	281 (18.56)	51
	75-84	7,482	96 (1.28)	1,264 (16.89)	80 (6.33)	45
	85+	577	7 (1.21)	138 (23.92)	5 (3.62)	52
<b>2012</b>	40-54	36,943	153 (0.41)	342 (0.93)	92 (26.90)	53
	55-64	24,885	296 (1.19)	958 (3.85)	217 (22.65)	53
	65-74	14,885	306 (2.06)	1,325 (8.90)	236 (17.81)	58
	75-84	6,775	93 (1.37)	1,140 (16.83)	81 (7.11)	52
	85+	502	3 (0.60)	112 (22.31)	3 (2.68)	53
<b>2013</b>	40-54	36,843	118 (0.32)	341 (0.93)	79 (23.17)	56
	55-64	25,974	285 (1.10)	1,026 (3.95)	223 (21.73)	51
	65-74	17,627	342 (1.94)	1,696 (9.62)	277 (16.33)	55
	75-84	6,337	93 (1.47)	1,007 (15.89)	76 (7.55)	52
	85+	1,702	6 (0.35)	420 (24.68)	4 (0.95)	49
<b>2014</b>	40-54	31,360	80 (0.26)	283 (0.90)	51 (18.02)	53
	55-64	21,679	212 (0.98)	856 (3.95)	169 (19.74)	54
	65-74	14,237	248 (1.74)	1,421 (9.98)	220 (15.48)	58
	75-84	5,606	73 (1.30)	949 (16.93)	58 (6.11)	52
	85+	1,465	5 (0.34)	376 (25.67)	5 (1.33)	75
<b>2015</b>	40-54	38,246	108 (0.28)	369 (0.96)	69 (18.70)	50
	55-64	29,863	329 (1.10)	1,357 (4.54)	277 (20.41)	57
	65-74	17,556	334 (1.90)	1,739 (9.91)	285 (16.39)	60
	75-84	6,893	88 (1.28)	1,092 (15.84)	75 (6.87)	59
	85+	2,142	11 (0.51)	493 (23.02)	10 (2.03)	41
<b>2016</b>	40-54	45,117	103 (0.23)	480 (1.06)	74 (15.42)	62
	55-64	39,284	426 (1.08)	1,847 (4.70)	348 (18.84)	58
	65-74	23,140	455 (1.97)	2,450 (10.59)	393 (16.04)	66
	75-84	8,464	115 (1.36)	1,387 (16.39)	96 (6.92)	53
	85+	2,085	23 (1.10)	552 (26.47)	19 (3.44)	53
<b>2017</b>	40-54	59,421	155 (0.26)	790 (1.33)	113 (14.30)	54
	55-64	55,447	518 (0.93)	2,904 (5.24)	452 (15.56)	58
	65-74	56,885	976 (1.72)	6,646 (11.69)	860 (12.94)	61
	75-84	20,594	253 (1.23)	3,494 (16.97)	227 (6.50)	59
	85+	4,735	21 (0.44)	1,100 (23.23)	19 (1.73)	49

Table B. 4: Annual Frequency of PSA Testing and Subsequent Prostate Biopsy, Stratified by Race

Year	Race	Number of PSA Tests	Biopsy or MRI within 180d	PSA test >4	PSA test >4 and biopsy or MRI within 180d	Mean time between all PSA tests and biopsy or MRI, d
			No. (%)	No. (%)	No. (%)	
2011	White	73,519	787 (1.07)	3,166 (4.31)	544 (17.18)	51
	Black	10,750	145 (1.35)	571 (5.31)	120 (21.02)	53
	Asian	3,662	24 (0.66)	109 (2.98)	21 (19.27)	53
	Hispanic	10,822	110 (1.02)	425 (3.93)	87 (20.47)	56
	Other	9,994	105 (1.05)	488 (4.88)	74 (15.16)	53
2012	White	55,222	571 (1.03)	2,530 (4.58)	413 (16.32)	54
	Black	8,400	94 (1.12)	422 (5.02)	77 (18.25)	60
	Asian	3,207	20 (0.62)	116 (3.62)	13 (11.21)	54
	Hispanic	8,682	79 (0.91)	381 (4.39)	58 (15.22)	51
	Other	8,479	87 (1.03)	428 (5.05)	68 (15.89)	57
2013	White	55,982	543 (0.97)	2,710 (4.84)	415 (15.31)	52
	Black	8,921	112 (1.26)	567 (6.36)	96 (16.93)	56
	Asian	3,482	23 (0.66)	161 (4.62)	18 (11.18)	58
	Hispanic	9,755	74 (0.76)	481 (4.93)	58 (12.06)	55
	Other	10,343	92 (0.89)	571 (5.52)	72 (12.61)	58
2014	White	44,709	346 (0.77)	2,218 (4.96)	280 (12.62)	54
	Black	6,602	79 (1.20)	425 (6.44)	65 (15.29)	55
	Asian	3,217	22 (0.68)	174 (5.41)	19 (10.92)	69
	Hispanic	9,454	75 (0.79)	472 (4.99)	60 (12.71)	57
	Other	10,365	96 (0.93)	596 (5.75)	79 (13.26)	57
2015	White	54,298	503 (0.93)	2,763 (5.09)	407 (14.73)	57
	Black	8,722	111 (1.27)	559 (6.41)	99 (17.71)	56
	Asian	4,507	26 (0.58)	201 (4.46)	21 (10.45)	54
	Hispanic	13,596	108 (0.79)	726 (5.34)	87 (11.98)	62
	Other	13,577	122 (0.90)	801 (5.90)	102 (12.73)	58
2016	White	66,261	636 (0.96)	3,593 (5.09)	509 (14.17)	62
	Black	11,835	163 (1.38)	931 (7.87)	144 (15.47)	62
	Asian	5,451	30 (0.55)	211 (3.87)	25 (11.85)	52
	Hispanic	15,484	109 (0.70)	800 (5.17)	100 (12.50)	62
	Other	19,059	184 (0.97)	1,181 (6.20)	152 (12.87)	59
2017	White	99,759	956 (0.96)	6,992 (7.01)	821 (11.74)	56
	Black	16,340	228 (1.40)	1,541 (9.43)	202 (13.11)	55
	Asian	7,764	46 (0.59)	521 (6.71)	41 (7.87)	67
	Hispanic	32,040	277 (0.86)	2,526 (7.88)	246 (9.74)	70
	Other	41,149	416 (1.01)	3,354 (8.15)	361 (10.76)	60

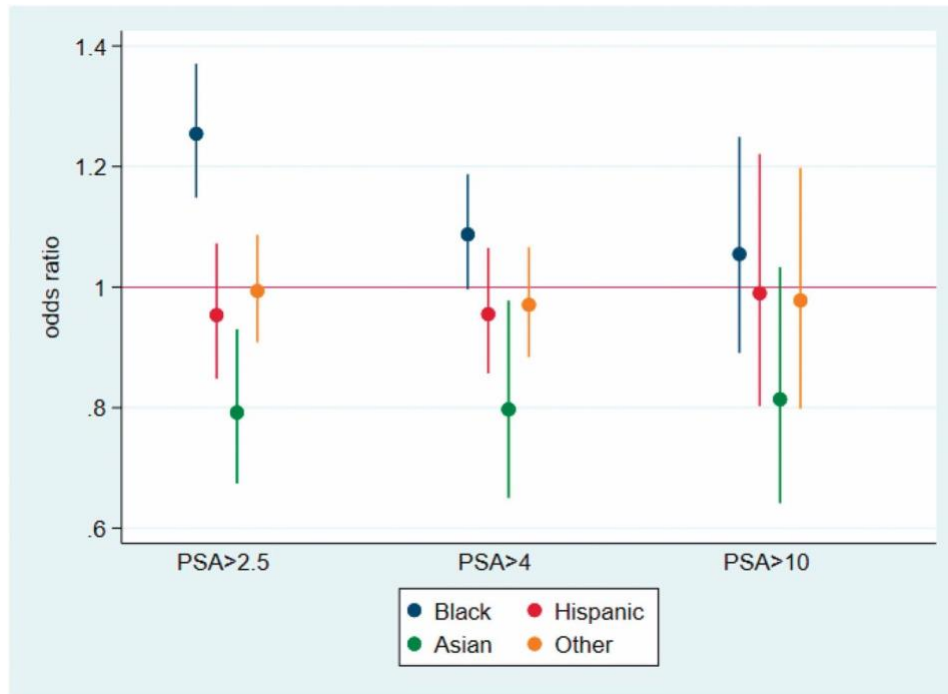


Figure B. 1: Odds ratio of subsequent prostate MRI or biopsy by PSA score

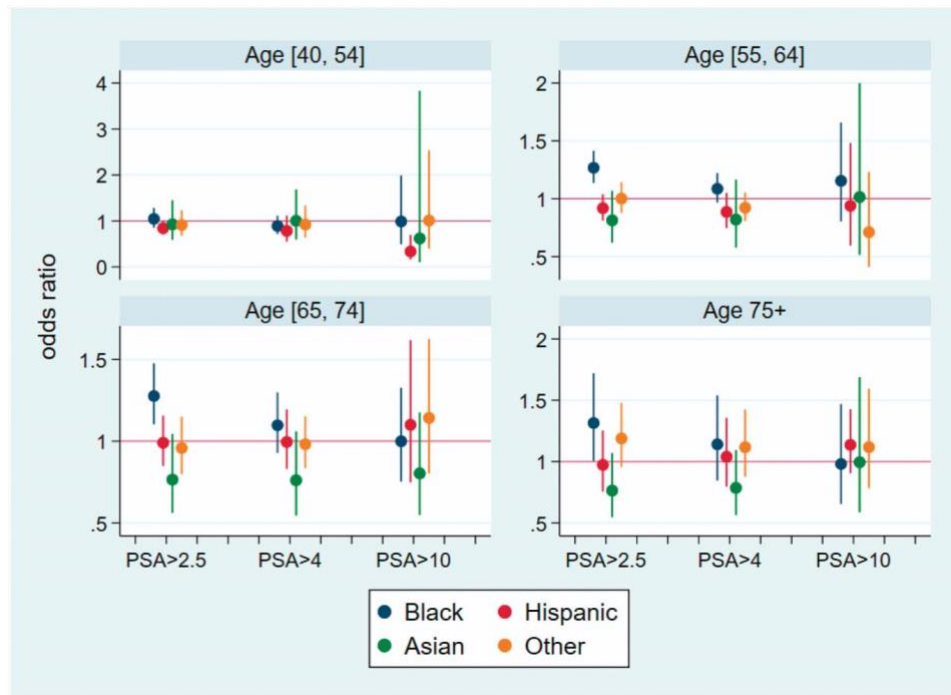


Figure B. 2: Odds ratio of subsequent prostate MRI or biopsy by age and PSA score

Table B. 5: Bivariate models of patients undergoing either a prostate biopsy or prostate MRI stratified by PSA level

	<b>PSA &gt; 2.5</b>	<b>PSA &gt; 4</b>	<b>PSA &gt; 10</b>	<b>PSA &gt; 2.5</b>	<b>PSA &gt; 4</b>	<b>PSA &gt; 10</b>
PSA > 2.5	67.60*** [56.76, 80.51]					
PSA > 4		78.60*** [70.58, 87.54]				
PSA > 10			29.52*** [26.28, 33.17]			
Black				1.328*** [1.174, 1.502]	1.158* [1.014, 1.322]	1.124 [0.918, 1.376]
Hispanic				0.823* [0.704, 0.962]	0.826* [0.702, 0.972]	0.912 [0.750, 1.109]
Asian				0.711* [0.539, 0.939]	0.719* [0.540, 0.957]	0.769 [0.562, 1.051]
Other				0.897** [0.834, 0.964]	0.847*** [0.784, 0.914]	0.933 [0.820, 1.061]
R2	0.277	0.333	0.078	0.002	0.002	0.001
No. of observations	765,409	765,409	765,409	100,960	43,711	7,808

Table B. 6: Bivariate models of patients undergoing either a prostate biopsy or prostate MRI stratified by PSA level for ages 40-54

	<b>PSA &gt; 2.5</b>	<b>PSA &gt; 4</b>	<b>PSA &gt; 10</b>	<b>PSA &gt; 2.5</b>	<b>PSA &gt; 4</b>	<b>PSA &gt; 10</b>
PSA > 2.5	139.2*** [108.2, 178.9]					
PSA > 4		222.4*** [189.5, 261.1]				
PSA > 10			137.7*** [104.9, 180.7]			
Black				1.041 [0.856, 1.266]	0.887 [0.713, 1.104]	1.005 [0.513, 1.968]
Hispanic				0.848 [0.707, 1.017]	0.785 [0.552, 1.117]	0.332** [0.158, 0.698]
Asian				0.927 [0.592, 1.451]	1.002 [0.595, 1.687]	0.564 [0.0797, 3.996]
Other				0.877 [0.680, 1.132]	0.899 [0.644, 1.255]	1.241 [0.596, 2.583]
R2	0.344	0.356	0.061	0.036	0.046	0.091
No. of observations	294,948	294,948	294,948	11,215	3,046	349

Table B. 7: Bivariate models of patients undergoing either a prostate biopsy or prostate MRI stratified by PSA level for ages 55-64

	<b>PSA &gt; 2.5</b>	<b>PSA &gt; 4</b>	<b>PSA &gt; 10</b>	<b>PSA &gt; 2.5</b>	<b>PSA &gt; 4</b>	<b>PSA &gt; 10</b>
PSA > 2.5	76.33*** [64.86, 89.84]					
PSA > 4		104.3*** [95.53, 113.8]				
PSA > 10			47.36*** [41.52, 54.03]			
Black				1.271*** [1.140, 1.416]	1.089 [0.970, 1.224]	1.141 [0.799, 1.629]
Hispanic				0.923 [0.814, 1.046]	0.891 [0.751, 1.058]	0.952 [0.606, 1.495]
Asian				0.815 [0.622, 1.067]	0.822 [0.579, 1.167]	1.02 [0.518, 2.006]
Other				0.936 [0.824, 1.064]	0.849* [0.744, 0.970]	0.630* [0.407, 0.973]
R2	0.297	0.374	0.0769	0.0132	0.0178	0.0323
No. of observations	233,355	233,355	233,355	28,699	10,320	1,337

Table B. 8: Bivariate models of patients undergoing either a prostate biopsy or prostate MRI stratified by PSA level for ages 65-74

	<b>PSA &gt; 2.5</b>	<b>PSA &gt; 4</b>	<b>PSA &gt; 10</b>	<b>PSA &gt; 2.5</b>	<b>PSA &gt; 4</b>	<b>PSA &gt; 10</b>
PSA > 2.5	42.07*** [36.53, 48.45]					
PSA > 4		55.57*** [50.03, 61.72]				
PSA > 10			20.19*** [17.05, 23.90]			
Black				1.261** [1.095, 1.453]	1.086 [0.919, 1.283]	1.025 [0.777, 1.350]
Hispanic				1.012 [0.865, 1.183]	1.016 [0.845, 1.222]	1.109 [0.755, 1.629]
Asian				0.771 [0.568, 1.047]	0.767 [0.555, 1.062]	0.792 [0.556, 1.130]
Other				0.984 [0.832, 1.164]	0.97 [0.844, 1.115]	1.038 [0.772, 1.396]
R2	0.227	0.314	0.0771	0.0169	0.0179	0.031
No. of observations	161,747	161,747	161,747	36,992	16,772	2,681

Table B. 9: Bivariate models of patients undergoing either a prostate biopsy or prostate MRI stratified by PSA level for ages 75 and above

	<b>PSA &gt; 2.5</b>	<b>PSA &gt; 4</b>	<b>PSA &gt; 10</b>	<b>PSA &gt; 2.5</b>	<b>PSA &gt; 4</b>	<b>PSA &gt; 10</b>
PSA > 2.5	25.95*** [19.57, 34.41]					
PSA > 4		28.40*** [23.85, 33.83]				
PSA > 10			13.12*** [11.23, 15.33]			
Black				1.332* [1.017, 1.743]	1.171 [0.868, 1.581]	0.99 [0.664, 1.478]
Hispanic				0.958 [0.746, 1.230]	1.025 [0.784, 1.339]	1.124 [0.894, 1.413]
Asian				0.773 [0.555, 1.078]	0.797 [0.571, 1.112]	1.005 [0.591, 1.711]
Other				1.12 [0.936, 1.339]	1.012 [0.820, 1.249]	1.023 [0.764, 1.372]
R2	0.151	0.202	0.0933	0.0201	0.019	0.0289
No. of observations	75359	75359	75359	23700	13391	3311

## APPENDIX C

Table C. 1: Estimated proportions of enrollees eligible for lung cancer screening stratified by demographic and geographic characteristics.

Characteristics	Eligible Population			<i>P</i> -value ( $\chi^2$ )	
	Medicare	Medicare Advantage	Commercial	Medicare vs. Medicare Advantage	Medicare Advantage vs. Commercial
<i>n</i> (eligible enrollees)	231,371	505,168	340,603		
95% CI	(223,989.7, 238,902.1)	(489,561.7, 521,067.7)	(330,142.7, 351,246.9)		
<b>Gender</b>				$< 0.001$	$< 0.001$
<i>Female</i>	52.1%	56.6%	48.9%		
<i>Male</i>	47.9%	43.4%	51.1%		
<b>Age</b>				$< 0.001$	$< 0.001$
<i>55 to 64</i>	12.6%	12.4%	83.3%		
<i>65 to 74</i>	74.7%	71.6%	15.8%		
<i>75 to 77</i>	12.7%	16.0%	0.9%		
<b>Race/ethnicity</b>					
<i>Non-Hispanic Black</i>	10.5%				
<i>Non-Hispanic White</i>	80.8%				
<i>Other</i>	8.8%				
<b>Region</b>				$< 0.001$	$< 0.001$
<i>Northeast</i>	17.2%	12.7%	7.7%		
<i>South</i>	41.4%	47.2%	47.2%		
<i>Midwest</i>	23.9%	20.6%	28.8%		
<i>West</i>	17.5%	19.5%	16.2%		
<b>Rural/Urban</b>				$< 0.001$	$< 0.001$
<i>Rural</i>	2.7%	1.8%	1.5%		
<i>Urban</i>	97.3%	98.2%	98.5%		

Table C. 2: Estimated proportions of screened enrollees stratified by demographic and geographic characteristics

Characteristics	Screened Population			P-value ( $\chi^2$ )	
	Medicare	Medicare Advantage	Commercial	Medicare vs. Medicare Advantage	Medicare Advantage vs. Commercial
<i>n</i> (screened enrollees) 95% CI	7,801 (7630.8, 7971.2)	23,058	5,966		
Gender				0.638	< 0.001
<i>Female</i>	49.4%	49.8%	43.2%		
<i>Male</i>	50.6%	50.2%	56.8%		
Age				0.015	< 0.001
<i>55 to 64</i>	18.8%	18.4%	82.6%		
<i>65 to 74</i>	72.1%	71.5%	17.1%		
<i>75 to 77</i>	9.1%	10.1%	0.3%		
Race/ethnicity					
<i>Non-Hispanic Black</i>	6.7%				
<i>Non-Hispanic White</i>	88.9%				
<i>Other</i>	4.4%				
Region				< 0.001	< 0.001
<i>Northeast</i>	23.9%	18.1%	12.6%		
<i>South</i>	37.1%	40.5%	40.4%		
<i>Midwest</i>	26.5%	25.8%	36.2%		
<i>West</i>	12.5%	15.6%	10.8%		
Rural/Urban				< 0.001	< 0.001
<i>Rural</i>	1.9%	1.4%	1.6%		
<i>Urban</i>	98.1%	98.6%	98.4%		

Note: The Medicare Advantage and Commercial groups are the 100% population of enrollees from the CDM's associated plans. The Medicare fee-for-service data is from a 5% sample of enrollees; thus, 95% CI are reported.

Table C. 3: Estimated low dose CT lung cancer screening rates by demographic and geographic characteristics.

	Sample Screening Rates			P-value ( $\chi^2$ )	
	Medicare	Medicare Advantage	Commercial	Medicare vs. Medicare Advantage	Medicare Advantage vs. Commercial
<i>n</i> (eligible enrollees)	231,371	505,168	340,603		
95% CI	(223,989.7, 238,902.1)	(489,561.7, 521,067.7)	(330,142.7, 351,246.9)		
<b>Gender</b>					
<i>Female</i>	3.19% (3.19%, 3.20%)	4.02% (4.01%, 4.02%)	1.55% (1.55%, 1.55%)	< 0.001	< 0.001
<i>Male</i>	3.57% (3.56%, 3.57%)	5.28% (5.28%, 5.28%)	1.95% (1.95%, 1.95%)	< 0.001	< 0.001
<b>Age</b>					
<i>55 to 64</i>	5.03% (5.03%, 5.04%)	6.77% (6.77%, 6.78%)	1.74% (1.74%, 1.74%)	< 0.001	< 0.001
<i>65 to 74</i>	3.26% (3.25%, 3.25%)	4.56% (4.56%, 4.56%)	1.89% (1.89%, 1.89%)	< 0.001	< 0.001
<i>75 to 77</i>	2.41% (2.41%, 2.41%)	2.87% (2.87%, 2.87%)	0.63% (0.63%, 0.64%)	< 0.001	< 0.001
<b>Race/ethnicity</b>					
<i>Non-Hispanic Black</i>	2.17% (2.17%, 2.17%)				
<i>Non-Hispanic White</i>	3.71% (3.71%, 3.71%)				
<i>Other</i>	1.68% (1.68%, 1.68%)				
<b>Region</b>					
<i>Northeast</i>	4.69% (4.69%, 4.70%)	6.52% (6.51%, 6.52%)	2.87% (2.87%, 2.87%)	< 0.001	< 0.001
<i>South</i>	3.02% (3.02%, 3.02%)	3.92% (3.92%, 3.93%)	1.50% (1.50%, 1.50%)	< 0.001	< 0.001
<i>Midwest</i>	3.74% (3.74%, 3.74%)	5.70% (5.70%, 5.71%)	2.20% (2.20%, 2.20%)	< 0.001	< 0.001
<i>West</i>	2.42% (2.41%, 2.42%)	3.65% (3.64%, 3.65%)	1.16% (1.16%, 1.16%)	< 0.001	< 0.001
<b>Rural/Urban</b>					
<i>Rural</i>	2.38% (2.38%, 2.38%)	3.56% (3.56%, 3.56%)	1.88% (1.88%, 1.88%)	< 0.001	< 0.001
<i>Urban</i>	3.401% (3.40%, 3.40%)	4.58% (4.58%, 4.59%)	1.75% (1.75%, 1.75%)	< 0.001	< 0.001
<b>Overall</b>	3.37% (3.27%, 3.48%)	4.56% (4.43%, 4.71%)	1.75% (1.70%, 1.81%)		

Table C. 4: Comparison of lung cancer screening rates of eligible enrollees aged 55-77 by insurance type.

Comparisons	<i>n</i> (eligible enrollees)	Overall Sample Screening Rates	<i>P</i> -value ( $\chi^2$ )
a.			< 0.001
<i>Medicare Advantage</i>	505,168	4.56% (4.43%, 4.71%)	
<i>Commercial</i>	340,603	1.75% (1.70%, 1.81%)	
b.			< 0.001
<i>Medicare Advantage</i>	505,168	4.56% (4.43%, 4.71%)	
<i>Medicare FFS</i>	231,371	3.37% (3.27%, 3.48%)	
c.			< 0.001
<i>Medicare (FFS + Medicare Advantage)</i>	736,539	4.19% (4.06%, 4.32%)	
<i>Commercial</i>	340,603	1.75% (1.70%, 1.81%)	
d.			0.159
<i>Medicare Advantage + Commercial (CDM)</i>	845,771	3.43% (3.33%, 3.54%)	
<i>Medicare (5% RIF)</i>	231,371	3.37% (3.27%, 3.48%)	
e.			< 0.001
<i>Medicare FFS</i>	231,371	3.37% (3.27%, 3.48%)	
<i>Commercial</i>	340,603	1.75% (1.70%, 1.81%)	

Table C. 5: Estimated proportions of enrollees eligible for lung cancer screening stratified by demographic and geographic characteristics.

Characteristics	Eligible Population			P-value ( $\chi^2$ )	
	Medicare	Medicare Advantage	Commercial	Medicare vs. Medicare Advantage	Medicare Advantage vs. Commercial
<i>n</i> (eligible enrollees) 95% CI	70,562 (66,223.6, 74,900.2)	157,013 (146,987.4, 167,037.9)	175,547 (168,292, 182,802.1)		
Gender				< 0.001	< 0.001
<i>Female</i>	50.3%	54.1%	44.1%		
<i>Male</i>	49.7%	45.9%	55.9%		
Age				< 0.001	< 0.001
<i>55 to 64</i>	19.1%	18.0%	89.4%		
<i>65 to 74</i>	79.1%	79.5%	10.5%		
<i>75 to 77</i>	1.8%	2.5%	0.1%		
Race/ethnicity					
<i>Non-Hispanic Black</i>	11.0%				
<i>Non-Hispanic White</i>	75.6%				
<i>Other</i>	13.4%				
Region				< 0.001	< 0.001
<i>Northeast</i>	30.5%	20.3%	14.9%		
<i>South</i>	27.2%	36.2%	38.3%		
<i>Midwest</i>	13.7%	9.3%	17.5%		
<i>West</i>	28.5%	34.3%	29.4%		

Table C. 6: Proportions of screened enrollees stratified by demographic and geographic characteristics

Characteristics	Screened Population			P-value ( $\chi^2$ )	
	Medicare	Medicare Advantage	Commercial	Medicare vs. Medicare Advantage	Medicare Advantage vs. Commercial
<i>n</i> (screened enrollees)	3,111	8,416	2,409		
95% CI	(3004.1, 3,217.9)				
Gender				0.626	< 0.001
<i>Female</i>	48.4%	49.0%	43.9%		
<i>Male</i>	51.6%	51.0%	56.1%		
Age				0.008	< 0.001
<i>55 to 64</i>	17.5%	15.8%	82.2%		
<i>65 to 74</i>	73.0%	73.5%	17.5%		
<i>75 to 77</i>	9.5%	10.7%	0.3%		
Race/ethnicity					
<i>Non-Hispanic Black</i>	7.6%				
<i>Non-Hispanic White</i>	86.7%				
<i>Other</i>	5.7%				
Region				< 0.001	< 0.001
<i>Northeast</i>	39.3%	27.4%	21.9%		
<i>South</i>	25.5%	35.0%	34.0%		
<i>Midwest</i>	18.9%	14.7%	27.7%		
<i>West</i>	16.3%	22.8%	16.4%		

Note: The Medicare Advantage and Commercial groups are the 100% population of enrollees from the CDM's associated plans. The Medicare fee-for-service data is from a 5% sample of enrollees; thus, 95% CI are reported.

Table C. 7: Estimated low dose CT lung cancer screening rates by demographic and geographic characteristics

	Sample Screening Rates			P-value ( $\chi^2$ )	
	Medicare	Medicare Advantage	Commercial	Medicare vs. Medicare Advantage	Medicare Advantage vs. Commercial
<i>n</i> (eligible enrollees) 95% CI	70,562 (66,223.6, 74,900.2)	157,013 (146,987.4, 167,037.9)	175,547 (168,292, 182,802.1)		
<b>Gender</b>					
<i>Female</i>	4.24% (4.24%, 4.25%)	4.86% (4.86%, 4.86%)	1.37% (1.37%, 1.37%)	< 0.001	< 0.001
<i>Male</i>	4.58% (4.57%, 4.58%)	5.95% (5.95%, 5.95%)	1.38% (1.38%, 1.38%)	< 0.001	< 0.001
<b>Age</b>					
<i>55 to 64</i>	4.08% (4.08%, 4.09%)	4.77% (4.77%, 4.77%)	1.26% (1.26%, 1.26%)	0.002	< 0.001
<i>65 to 74</i>	4.10% (4.10%, 4.10%)	4.99% (4.99%, 4.99%)	2.29% (2.29%, 2.29%)	< 0.001	< 0.001
<i>75 to 77</i>	23.54% (23.54%, 23.55%)	23.36% (23.35%, 23.37%)	5.55% (5.55%, 5.56%)	0.843	< 0.001
<b>Race/ethnicity</b>					
<i>Non-Hispanic Black</i>	3.06% (3.06%, 3.06%)				
<i>Non-Hispanic White</i>	5.06% (5.06%, 5.06%)				
<i>Other</i>	1.86% (1.86%, 1.87%)				
<b>Region</b>					
<i>Northeast</i>	5.66% (5.66%, 5.67%)	7.26% (7.26%, 7.26%)	2.02% (2.02%, 2.02%)	< 0.001	< 0.001
<i>South</i>	4.13% (4.12%, 4.13%)	5.19% (5.19%, 5.20%)	1.22% (1.22%, 1.22%)	< 0.001	< 0.001
<i>Midwest</i>	6.06% (6.06%, 6.06%)	8.54% (8.53%, 8.54%)	2.17% (2.17%, 2.17%)	< 0.001	< 0.001
<i>West</i>	2.52% (2.52%, 2.52%)	3.56% (3.56%, 3.56%)	0.77% (0.77%, 0.77%)	< 0.001	< 0.001
<b>Overall</b>	4.4% (4.2%, 4.7%)	5.4% (5.0%, 5.7%)	1.4% (1.3%, 1.4%)		

Table C. 8: Comparison of lung cancer screening rates of enrollees aged 55-77 by insurance type

Comparisons	<i>n</i> (eligible enrollees)	Overall Sample Screening Rates	<i>P</i> -value ( $\chi^2$ )
a.			< 0.001
<i>Medicare Advantage</i>	157,013	5.4% (5.0%, 5.7%)	
<i>Commercial</i>	175,547	1.4% (1.3%, 1.4%)	
b.			< 0.001
<i>Medicare Advantage</i>	157,013	5.4% (5.0%, 5.7%)	
<i>Medicare FFS</i>	70,562	4.4% (4.2%, 4.7%)	
c.			< 0.001
<i>Medicare (FFS + Medicare Advantage)</i>	227,575	5.1% (4.8%, 5.4%)	
<i>Commercial</i>	175,547	1.4% (1.3%, 1.4%)	
d.			< 0.001
<i>Medicare Advantage + Commercial (CDM)</i>	332,560	3.3% (3.1%, 3.4%)	
<i>Medicare (5% RIF)</i>	70,562	4.4% (4.2%, 4.7%)	
e.			< 0.001
<i>Medicare FFS</i>	70,562	4.4% (4.2%, 4.7%)	
<i>Commercial</i>	175,547	1.4% (1.3%, 1.4%)	

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