Spectrum Allocation to Public Operators: A Structural Analysis of Set-Asides versus Subsidies in Indian Telecom Auctions

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Abstract

We study spectrum auctions in India, where private operators acquire licenses through simultaneous multiple-round auctions (SMRA) while an all-India license is set-aside for the public operator. We quantify the government revenue loss under the set-aside and analyze the trade-off between revenue and public service coverage under counterfactual subsidized-auction designs. Using a structural model of bidding accounting for both the stand-alone values and inter-license complementarities, we identify the model parameters from bidding behavior across licenses and rounds. We also introduce a railway connectivity-based index to capture complementarities for India. Counterfactual simulations show that allowing the public operator to bid without subsidy raises expected revenue by 7% and find an inverted U-shaped relationship between the public operators winning probability and circle level price changes, driven by heterogeneity in bidder valuations and complementarities. We also demonstrate that a location-based subsidy can yield higher revenues for a given level of coverage compared to a nationwide subsidy.

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1 Introduction

The radio frequency spectrum, which spans frequencies from 3 kHz to 300 GHz, is a vital resource for mobile communication technology. Although it is not a depletable resource, the government strictly regulates its generation and transmission to prevent interference between users. This makes radio spectrums scarce and rivalrous in nature, necessitating allocation by regulatory agencies to ensure their efficient and effective use. The allocation mechanism for such scarce public resources, like the radio frequency spectrum, is a significant concern for economists and policymakers. The mechanism must consider several factors, including the regulator's revenue objectives, protection against anti-competitive behavior, and the impact on downstream markets. Policymakers globally have experimented with various allocation methods to maximize social returns. While earlier methods included beauty contests, auctions have become the predominant mechanism for spectrum allocation, displacing earlier administrative processes. Two widely used auction formats for spectrum allocation globally are Simultaneous Ascending Price Auctions (SMRA) and Combinatorial Clock Auctions (CCA), though both have been central to political and economic debates for decades.

India's telecom sector is one of the largest in terms of subscriber base and one of the fastest-growing in the world. Over the past decade, mobile communication technology has experienced rapid growth in the country. During the first decade of the 21st century, telecom subscribers grew by an impressive 33% annually, equivalent to an addition of 20 million subscribers per month (Competition Commission of India (2021)). This growth reflects the increasing demand for connectivity and highlights the critical role of the telecom sector in India's economic and technological development. In terms of revenue, the sector generated substantial financial returns, making it a pivotal contributor to the country's GDP. As of 2025, the telecom market is projected to grow even further, driven by the adoption of 5G technology and increasing internet penetration in rural areas.

The Indian spectrum market, though similar in certain aspects, faces a different set of challenges in comparison to its counterparts in the developed world. India has both private and public telecom service providers, in contrast to the markets that the previous literature has predominantly studied. This combination of both private and public players makes the spectrum allocation and market design problem interesting. India's telecom market includes two state-owned service providers: Bharat Sanchar Nigam Limited (BSNL) and Mahanagar Telephone Nigam Limited (MTNL). MTNL's operations were limited to two bid cities, Delhi and Mumbai, while BSNL catered to other geographical areas. In contrast, the private providers in India received licenses to operate in different service areas from the regulatory authority through an SMRA, the all-India license was granted to the public service providers at a price determined by the spectrum auction, without them directly participating in the auctions.

The Indian government initially allocated spectrum administratively, selecting enterprises deemed most capable of improving the country's telecom infrastructure. However, the Telecommunication Regulatory Authority of India (TRAI) adopted SMRA auctions in 2010, which marked a turning point. The 3G spectrum blocks were auctioned separately in all circles, generating approximately $11 billion or INR 50968.37 crores in total bids from private operators for wireless spectrum . All spectrum blocks offered were sold, and no single company succeeded in acquiring spectrum in all the service areas, ensuring no private operator had national-level coverage. However, unlike the private operators, the public operators did not participate in the 2010 auction. Instead, they were allocated nationwide spectrum rights at a fixed fee to fulfill the government's Universal Service Obligation. This allocation mechanism used for the public operator is referred to as a set-aside, where certain portions of the auctioned goods or contracts are reserved for a specific group of participants.

Set-asides are typically used to protect small firms, where they can increase participation among small businesses but reduce competition by excluding larger firms. This can potentially lead to an efficiency loss and a reduction in auction revenue due to a reduction in competition (Hyndman and Parmeter (2015)). Another common method for the auctioneer to achieve distributional goals is through a subsidy, where discounts are provided to preferred bidders, allowing all bidders to participate. Subsidies, when optimally designed, can achieve the same distributional goals with higher revenue and reduced efficiency losses. Subsidy programs are more flexible and beneficial in settings where preserving competition and maximizing revenue are both critical. Athey et al. (2013) find that subsidies to small bidders are a more effective means of achieving distributional goals in the context of the US Forest Service timber sale program.

This paper studies the 2010 3G spectrum auction in India and compares counterfactual subsidy-based allocation mechanisms for the public operator to the status quo set aside. We measure the implicit subsidy to public operators by estimating the governments revenue loss from the set-aside and comparing the status quo to a counterfactual in which public operators bid alongside private firms, with their allocated spectrum licenses also being offered in the auction. We also explore counterfactual mechanisms where the public operators face a subsidized price with varying levels of discount, and investigate the trade-off between government revenue and the public provider's coverage, measured in terms of the expected proportion of the national population having access to the public operator's service, calculated using their circle-level winning probabilities. We use a stylized structural model of bidding behavior suitable for spectrum auctions in India. Our model follows that of Xiao and Yuan (2022a) and allows for both bidder-license specific stand-alone valuation and also synergies across licenses, capturing the incentives of the bidders to form packages of licenses with strong complementarities.

To our knowledge, this paper is the first structural analysis of spectrum auctions in India. Our study departs from the prior literature in two important aspects. First, most existing work compares set-asides and subsidies in the context of protecting small bidders or new entrants, our empirical setting involves Indian public telecom service providers, both large incumbents with substantial market shares during the period of study and a long legacy of serving the Indian market. The primary policy objective of the set-aside in our setting is to ensure nationwide network accessibility through these public operators. We therefore examine alternative subsidy-based mechanisms that may enhance government revenue while preserving the public operators' probability of winning across circles. Second, we extend earlier findings on set-asides versus subsidies to empirical settings that allow license complementarities. We demonstrate that, in the presence of such complementarities, targeted subsidies that account for bidders incentives to form packages can achieve the same distributional goals while generating higher revenues. Thus, our paper highlights why the nature of these synergies must be carefully considered when designing protectionist policies.

We estimate the underlying valuation of private bidders, which includes both bidder-license specific stand-alone value and license complementarities capturing the synergies across licenses. The paper follows a two-step identification strategy: the parameters governing the complementarity values are first identified from observed bidding behavior across licenses and rounds, and then estimated using a moment inequality-based approach within a revealed-preference framework. We assume bidders play a Bayesian Nash Equilibrium in strategies, with beliefs about winning probabilities in each round estimated using a logit specification. In the second stage, the mean bidder-license level stand-alone values are estimated using a log-likelihood approach under suitable parametric assumptions, along with the bounds on the unobserved private value component. We introduce a new complementarity index suitable for our empirical setting in India, utilizing railway connectivity data across circles.

The estimated structural parameters are used to simulate market outcomes for both the status quo benchmark and counterfactual settings. We simulate the outcomes of each auction by computing the minimum bidding set for every bidder in each round, mimicking the rules of the SMRA auction, and continue until there is no excess demand for spectrum in any circle. The minimum bidding set in each round finds the set of licenses that a bidder should always bid on, given its history. The process takes into consideration the bidders' belief of winning a license, conditional on the history, as well as the complementarities across licenses. The benchmark simulation shows that our model captures the observed outcomes well at the mean, and we compare the distributions of the counterfactual outcomes with the benchmark outcomes for our analysis.

We observe that the public operators' participation in the auction without any price discount increases the mean national revenue from the auctions by 7%, illustrating how the status quo set aside reduces price competition. Analyzing the counterfactual outcomes across the circles, we also document an inverted U-shaped relationship between the public operator's probability of winning and the circle-level increase in price. We explain this observed relationship using both heterogeneity in the public operator's valuations across circles and the nature of license complementarities in our empirical setting. We observe that the public operators' participation has a negligible revenue effect in many licenses where it is a strong bidder, but also a negligible to some negative revenue effect in circles where they are weak. This is due to the fact that the number of possible winners in these circles increases in the counterfactual, without the public operator providing any credible competition.

However, we find that the licenses generating the largest revenue gains from public operators' participation are those characterized by high complementarities with other circles where the public operator is dominant in terms of their stand-alone valuations, due to their geographical locations. The spatial distribution of stand-alone valuation and the complementarities across licenses thus leads to intense competition among the bidders in these circles in our counterfactual, characterized by a substantial increase in final prices and moderate winning probabilities for the public operator.

The counterfactual results indicate that the public operator might not require protection in all parts of India. In this paper, we find that providing a subsidy to bidders without considering this can yield undesirable outcomes. We proceed with two alternative counterfactual subsidy rules: I) **All-India**, where public operators receive a price discount on all circles, and II) **Location-based**, where public operators are provided a price discount for specific geographical clusters that can potentially be beneficial for package formation, as indicated by our counterfactual simulations. This exercise is motivated by our finding that, in the counterfactual without price discounts, public operators tend to perform well in circles with relatively low stand-alone valuations but are geographically adjacent to their other strongholds, and we exclude them from the subsidy in the location-based mechanism. Conversely, they fare worse in circles with relatively high stand-alone valuations that lack such geographic synergies, and are included for subsidy in the location-based mechanism.

Comparing the two mechanisms with varying levels of subsidies, we find that a location-based subsidy dominates an all-India subsidy in terms of the national revenue, while achieving very similar distributional goals for higher levels of subsidy. The All-India subsidy shows a steeper trade-off between revenue and coverage when compared to the location-based subsidy, with the revenue falling sharply for a marginal increase in the coverage beyond 80% as price discounts are provided to the public operator under this mechanism to circles where they are not required to improve the public operator's winning probabilities. We also find that both the mechanisms achieve an expected coverage of around 97% of the national population at a price subsidy of 25%, but the national revenue under an all-India subsidy approaches the national revenue under that of a set aside, while the targeted subsidy still achieves a statistically significant higher level of revenue.

The rest of the paper is structured as follows: we provide the institutional details in Section 2, where we describe the auction details and the market structure, including the role of the public operators. The data sources and details, including some summary statistics, are provided in Section 3. In Section 3 we introduce our model framework, including the model primitives we identify and estimate in Section 5. The counterfactual simulation procedure and the results are discussed in Section 6.

Literature Review: Auction theory highlights that the revenue effects of set-asides and subsidies depend critically on the relative strength of targeted and non-targeted bidders. When targeted bidders valuations are close to those of non-targeted bidders, subsidies implemented as bid credits can induce more aggressive bidding by the targeted group, increasing head-to-head competition and pushing prices up, as shown by Myerson (1981) and McAfee and McMillan (1989). Empirical evidence supports these theoretical predictions. Athey et al. (2013) structurally estimate a model of bidder entry and bidding from unrestricted sealed-bid auctions to compare the two instruments. They find that set-asides increase target bidder participation but reduce efficiency and revenue by excluding high-value competitors, whereas a modest subsidy can match distributional goals while increasing revenue and nearly eliminating efficiency loss.

Similarly, Marion (2007) and Krasnokutskaya and Seim (2011) study bid subsidies in California highway procurement auctions and find mixed cost effects: Marion reports a 3.8% increase in procurement costs due to reduced participation of large firms, while Krasnokutskaya and Seims structural estimates suggest a much smaller impact, under 1%. Hyndman and Parmeter (2015) estimates a structural SMRA model to evaluate the governments set-aside for new entrants and finds similar static trade-offs: set-asides guaranteed spectrum access for entrants and increased post-auction competition, but caused measurable efficiency losses and lower revenues. Most empirical studies on set-asides or subsidies focus on protecting small firms or new entrants and are set within an independent private values framework. This paper differs in two key respects. First, the public telecom operator BSNL, being a long-established, state-owned firm with a nationwide network, is neither a small company nor a new entrant to the Indian mobile market. Second, we examine set-asides and subsidies in an SMRA environment that allows for synergies across auctioned licenses, departing from the standard independent private values framework. While prior results on such protective policies have hinged mainly on the extent of bidder asymmetry, our findings highlight the additional importance of accounting for complementarities among auctioned objects in an SMRA setting. We show that the spatial distribution of bidders valuations plays a crucial role in determining the effectiveness of subsidies in our framework.

Hong and Shum (2003) presents an early structural model for ascending spectrum auctions, focusing on estimation challenges from multi-round formats. Most structural estimations of SMRA spectrum auctions have focused on the U.S. context, often analyzing FCC auction data to recover bidder valuations and quantify geographic complementarities across licenses. Fox and Bajari (2013) use a many-to-one matching framework with pairwise stability to measure complementarities and efficiency without requiring full bid data, while Xiao and Yuan (2022a) employ a moment-inequalities approach to separately identify stand-alone values and complementarity effects, showing how these influence exposure problems and package bidding outcomes. Our study is the first to conduct a structural analysis of an Indian spectrum SMRA auction. Methodologically, our framework is closest to Xiao and Yuan (2022a). We also propose a new complementarity index based on railway travel networks, which is suitable for our empirical setting in India, similar to indexes previously used by Fox and Bajari (2013). Despite a substantial body of work on auction design and policy, there is limited structural econometric analysis of Indian spectrum auctions compared to the extensive literature on U.S. and European markets.

Empirical studies of Indian spectrum auctions highlight the evolution of regulatory design and its impact on market efficiency. Prasad et al. (2016) provide an institutional analysis of India's transition from administrative spectrum assignment to market-based auctions, showing how regulatory reforms shaped competition and transparency. Kathuria et al. (2019) evaluate six major auctions conducted between 2010 and 2016 and find that while the 2010 3G and BWA auctions achieved strong revenues and participation, subsequent auctions suffered from inflated reserve prices and reduced competition. Complementing these findings, Christopher (2017) uses Department of Telecommunications auction data to show that the 2010 3G auction was the most successful, with later rounds exhibiting weaker demand due to high reserve prices and limited bidder interest.

2 Empirical Setting

2.1 Indian Telecom Market Structure

The Indian telecommunications sector represents one of the world's largest and most dynamic markets, characterized by a mix of state-owned incumbents and private competitors operating across diverse geographic regions. The market underwent significant liberalization beginning in the 1990s, transitioning from a government monopoly to a competitive landscape with multiple private operators. By 2010, the sector featured several major players including state-owned Bharat Sanchar Nigam Limited (BSNL) and Mahanagar Telephone Nigam Limited (MTNL), alongside private firms such as Bharti Airtel, Vodafone India, Idea Cellular, and several regional operators.

Geographically, India's telecom market is organized into 22 service areas known as telecom circles, which roughly correspond to states or combinations of smaller states. These circles vary substantially in terms of population, income levels, urbanization rates, and existing infrastructure. The market structure and competitive dynamics also differ considerably across circles, with major metropolitan areas featuring intense competition among multiple operators, while rural and less developed regions often have fewer active providers. The regulatory framework governing this market falls primarily under the Telecom Regulatory Authority of India (TRAI), established in 1997 to create and maintain fair competition while balancing carrier and consumer interests (Telecom Regulatory Authority of India, 2010). TRAI oversees spectrum allocation, licensing, tariff regulation, and quality of service standards. Additionally, operators face various universal service obligations designed to extend connectivity to underserved regions, though the specific requirements and enforcement mechanisms have evolved over time.

2.2 State-Owned Telecom Firms

BSNL and MTNL occupy a unique position in the Indian telecom landscape as state-owned enterprises with both commercial and social objectives. BSNL was formed in 2000 through the corporatization of the erstwhile Department of Telecom Services, inheriting a vast network infrastructure and nationwide presence, excluding Delhi and Mumbai. MTNL, established in 1986, operates exclusively in these two metropolitan areas, representing some of the most lucrative telecom markets in the country. As legacy carriers, these firms began with significant advantages, including established infrastructure, large customer bases, and substantial spectrum holdings. However, they also faced distinctive challenges stemming from their public sector status. These include higher operating costs attributable to larger workforces with government employment terms, bureaucratic decision-making processes that reduced agility in a rapidly evolving market, and political intervention in strategic and operational decisions.

The state-owned operators maintain an extensive rural presence, often serving areas that private firms consider economically unviable. This broader geographic coverage aligns with their social service mandate but creates financial strain due to lower average revenue per user (ARPU) in these regions. Additionally, these firms typically experience higher equipment maintenance costs due to aging infrastructure and face limitations in modernizing technology due to procurement regulations that apply to public sector enterprises. These factors contributed to a gradual decline in market share for BSNL and MTNL as private competitors expanded their networks and introduced newer technologies more rapidly. By 2010, the state operators were experiencing significant competitive pressure, particularly in urban and semi-urban areas, though they retained substantial subscriber bases in rural regions where private investment lagged.

2.3 2010 Spectrum Auction

The 2010 spectrum auction represented a pivotal moment in Indian telecommunications history, marking the country's first major allocation of 3G and 4G spectrum bands. The government employed a Simultaneous Multiple Round Ascending (SMRA) auction format, in which bidders could place bids on multiple license areas simultaneously across several rounds (Department of Telecommunications, 2010). This design allowed for price discovery while enabling bidders to adjust their strategies based on evolving prices and competitor behavior. The auction included spectrum in the 2100 MHz band for 3G services that we study in this paper where each operator bid for 5 MHz blocks. Circle-wise allocation enabled operators to bid selectively on regions aligned with their strategic priorities rather than requiring nationwide commitments.

In the SMRA auction format implemented, all the licenses were offered simultaneously with an ascending price in every clock round. Each bidder had to pay a money deposit to get eligibility points that determined their ability to bid, and to maintain eligibility, bidders had to remain active in each round by placing bids on licenses equal to a certain share of their eligibility points. The use of such eligibility points and activity rules is common in most SMRA auctions to implement straightforward bidding, so that bidders can't strategically wait for jump bidding in a circle. The circles were classified into three categories: A, B, and C, where category A circles are high revenue circles, category B are medium revenue ones, and category C are low revenue, smaller circles. The number of slots available in each circle varied between two to three private operators.

In each clockround, a minimum acceptable bid, which we will refer to as the clockround price in the rest of the paper. The bidders bid a yes or no, given the price, disclosing their willingness to pay the amount to acquire the particular license. If the number of willing buyers exceeds the number of blocks to be allocated in a particular circle, then the auction proceeds to the next clock round, with an increase in price, where the amount of increase depends on the round number and the excess demand. A set of provisional winners equal to the total number of spectrum blocks to be allocated in the circle is selected out of these willing buyers. In case no bids are received in the next round at the elevated price, the spectrums are awarded to these provisional winners. The process continued till no new bids are received in every auctioned circle.

A distinctive feature of this allocation process was the separate treatment of state-owned operators. While private firms competed in the auction, BSNL and MTNL received direct administrative allocations at prices equivalent to the highest winning bids in their respective operating areas, effectively excluding state firms from the competitive bidding process. The auction generated significant interest from private operators, resulting in intense bidding for licenses in major economic centers and metropolitan areas. Final prices varied substantially across circles, reflecting differences in market potential, existing competition, and strategic importance to bidders. All available spectrum was eventually allocated, with major private operators securing licenses in their priority markets.

3 Data

3.1 Data Sources and Structure

Our analysis incorporates data from multiple sources to construct a comprehensive dataset covering the 2010 Indian spectrum auction, operator characteristics, and market conditions. The primary auction data comes from the Department of Telecommunications of India [1], which maintains detailed records of bid histories, final allocations, and payment information for all participants across auctions. This includes round-by-round bidding decisions for all the bidders, round-level prices, provisional winning statuses, and final prices for each license area. The 2010 3G spectrum auctions saw intense competition among the bidders, where the auction lasted for 183 rounds, with a mean circle price of INR 765 crores ($167 million approx), and the maximum price going as high as INR 3350 crores ($732 million approx) (Appendix A).

We supplement the auction data with TRAI Subscription Reports and operational information from company annual reports and regulatory filings [2]. These sources provide operator-specific metrics such as subscriber base and the market shares across different telecom circles. We allow the bidder license specific mean stand-alone valuation to depend on the bidder and circle specific characteristics. Geographically, our dataset covers all 22 telecom circles in India. Infrastructure metrics include tower density per geographic area and existing network quality measures. These factors influence the cost of utilizing newly acquired spectrum, as operators with established infrastructure can more readily deploy new services without significant additional investment (Wallsten, 2013). We use the Indiastat data for the circle-level number of towers.

Operational metrics include market share percentages by circle, reflecting established customer bases and brand strength in specific regions. We also distinguish the bidders based on their incumbency status in every circle and allow their valuations and beliefs to depend on it. The value of spectrum licenses varies considerably across telecom circles due to differences in demographic composition, economic conditions, and infrastructure development. Our dataset includes several circle-level characteristics that influence spectrum valuations. Population size represents the most direct measure of market potential, with larger circles generally commanding higher valuations due to greater revenue opportunities. We utilize census data for total population figures, and urbanization ratios are calculated as the percentage of population residing in urban areas, serving as proxies for higher average revenue per user and lower infrastructure deployment costs. We create circle-level measures of these variables from census data by using information on the geographical boundaries for every circle.

Figure 1 shows the variation across telecom service providers in terms of their average market share and total subscription base across all circls in India. We see that private operators like Bharti, Reliance, Vodafone, Idea, and Tata have larger average market shares compared to other smaller operators. It can be noted that the public operator BSNL has a comparable average market share to some of these companies, though market shares varied widely across different circles. The above is also true for most of the large private operators, as shown by the whisker plot. We use existing

[1] https://dot.gov.in/spectrum

[2] http://www.trai.gov.in/

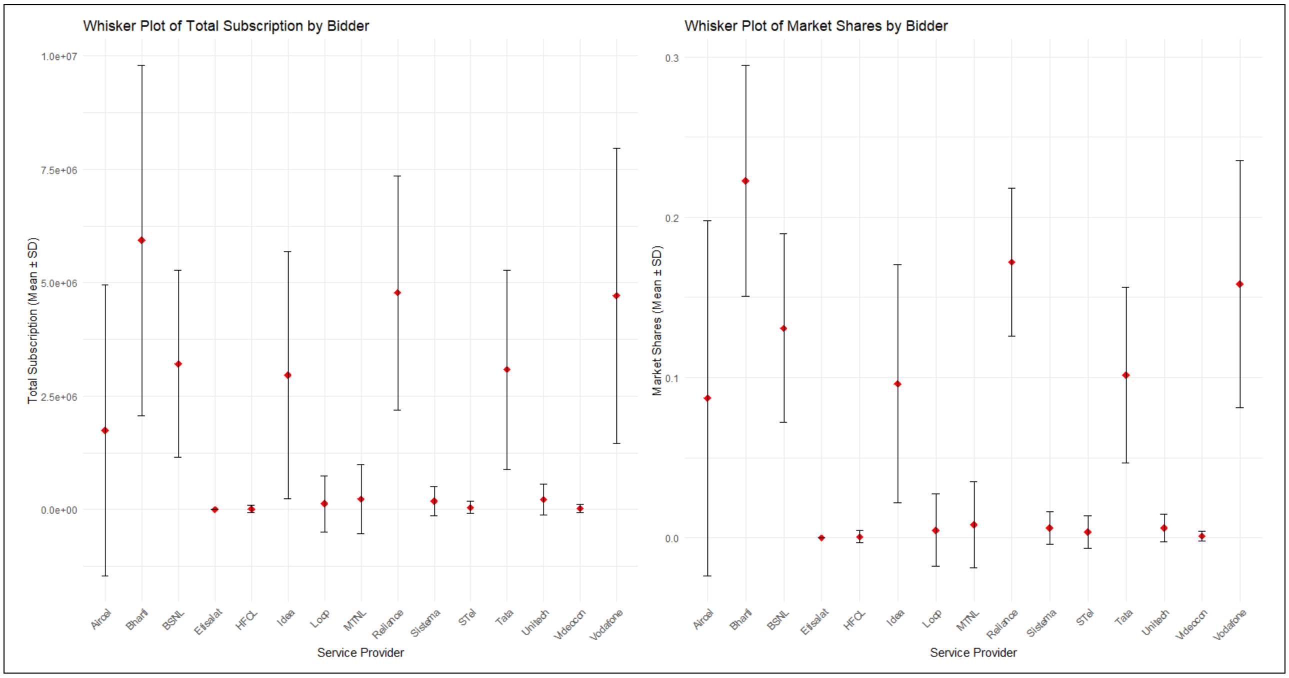


Figure 1: Whisker plot depicting Total Subscription and Market Shares for existing telecom service providers across all circles in India for the financial quarter ending March 2010. The plot illustrates the mean values and standard deviations in terms of absolute value for Total Subscription and Percentages for the Market Shares on the Y-axis, with the names of the individual service providers represented on the X-axis.

market shares, which also provide us with information regarding the incumbency status of all the firms in every circle as a determinant of the mean valuation for a bidder circle pair in our estimation procedure.

This paper introduces a pairwise license complementarity index for our empirical setting in India using railway connectivity data. We use structured information on train services operating within the Indian railway network, consisting of 4,024 records representing individual train services with basic route information, including origin and destination stations. The geographic coverage includes 390 unique railway stations distributed across the Indian railway network, comprising 373 origin stations and 372 destination stations. For each train in our data, we find out the identity of the circles it connects. This is done by mapping each trains route to the geographical locations of all the stations it serves. This allows us to compute, for any pair of circles, both the number of trains directly connecting them and the total volume of railway movements within those circles. These numbers are used to connect the complementarity index, as will be discussed in Section 4.

Service quality metrics are derived from TRAI's Quality of Service Analytics Portal (Telecom Regulatory Authority of India, 2011), which compiles regular performance reports submitted by operators. These include technical indicators such as call drop rates, connection success rates, and network availability statistics. We focus specifically on Base Transceiver Station (BTS) downtime percentages and voice quality measurements, which have direct implications for consumer experience and willingness to pay. We use two measures of the quality of telecommunication services in India: BTS downtime and good voice quality. BTS downtime in the telecommunications market

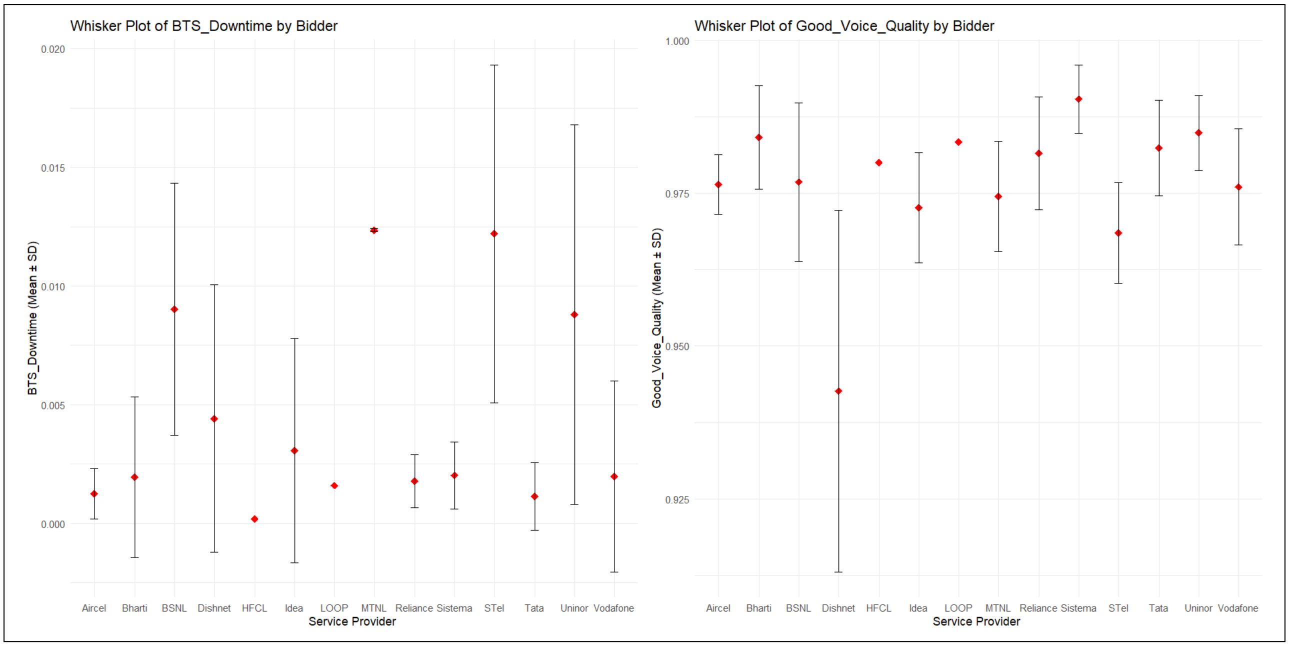


Figure 2: Whisker plot depicting BTS Downtime and Good Voice Quality for existing telecom service providers across all circles in India for the financial quarter ending March 2010. The plot illustrates the mean values and standard deviations (in percentages) of both metrics on the Y-axis, with the names of the individual service providers represented on the X-axis.

refers to the period during which a Base Transceiver Station (BTS) is non-operational or unable to provide services to its designated coverage area and is measured as the ratio of total downtime hours and the total hours in a period. TRAI Quality of Service Reports provides the data for both the measures of service quality.

BTS downtime is a key indicator of an operator's infrastructure reliability and quality of service, where increased downtime leads to dropped calls, poor connectivity, and degraded voice and data quality. The metric Good Voice Quality refers to the percentage of voice calls that meet or exceed a specified quality threshold. This assessment is typically based on parameters such as the Frame Erasure Rate (FER) and the Mean Opinion Score (MOS) [3]. These evaluations are crucial for ensuring that service providers maintain a high standard of voice communication quality for consumers. The Indian telecommunication market in 2010 exhibited significant heterogeneity in quality across providers, as shown in Figure 2. Telecommunication providers in India in 2010 differed significantly in terms of their quality with respect to these two measures. The public providers BSNL and MTNL perform worse with respect to other big private telecom providers in terms of their BTS Downtime except marginal ones like STel.

[3]See Appendix B for more details regarding construction of the measure

4 Model

We use a stylized model of firm bidding for the SMRA auction for spectrum licenses in India. The firm valuations have two components: the stand-alone valuations for every bidder for individual circles and the complementarity across licenses. Both components of the valuations are parameterized in our model. We assume a Perfect Bayesian Nash Equilibrium strategy for firm bidding. While the core Xiao and Yuan (2022b) framework provides the methodological foundation, necessary adaptations are made for the Indian context.

A set of bidders $i \in \mathcal{N}$ bids simultaneously on a set of licenses $l \in \mathcal{L}$ in an SMRA setting as described in Section 2.3. The auction proceeds over rounds t where each license in each round is associated with a price denoted by P_{lt}. Every service area is a different license on which the bidders are bidding simultaneously. In every round, bidders bid in the form of accepting or not accepting to buy a particular license l at the posted price P_{lt}. If the number of interested bidders for any license exceeds the number of eligible winners for that license, then the auction proceeds to round $t+1$, where all the licenses are put up for bidding with a revised price P_{lt+1}. A set of provisional winners is chosen from the willing bidders in round t, where the number of provisional winners in each license is equal to the number of possible winners in that license. If no new bidders are willing to bid for the license in the rounds following t at the adjusted price, the provisional winners get the particular license. The procedure follows until no new bids are received for any of the licenses.

Each bidder i has a stand-alone value for license l denoted by v_{il}. The stand-alone value of a bidder-license pair remains the same across rounds. Our model incorporates synergies across licenses using pairwise complementarities across licenses. The pairwise complementarity index for any two licenses l and l' is denoted by $\tau(l, l')$. The construction of this pairwise license complementarity index will be discussed later. The purpose of this index is to capture the proximity of two licenses in terms of the incentives of a bidder to include both of them simultaneously in their package. This complementarity allows for the value of holding two licenses simultaneously to be greater than the sum of their individual valuations. This captures the incentive of service providers to hold spectrum in geographically contiguous regions for seamless coverage and to reduce the operational cost of establishing a network. Operators may also want to consider holding circles with a high volume of inter-circle travel among their customer base to reduce costly roaming charges.

We denote a set of bidder-license specific characteristics X_{il}, which includes also bidder-specific and license-specific characteristics. The complementarity index $\tau(l, l')$ between licenses, the round license level price P_{lt}, and the bidder-license specific characteristics X_{il} are public information. In each round t, a bidder decides on a set of licenses B_{it} to bid on, and observes the set of licenses W_{it} where she is a provisional winner. Neither of them is observed by other bidders and is considered bidder i's private information along with the standalone private value component. The value of a set of licenses S for a bidder i is given by

$$V_i(S) = \sum_{l \in S} v_{il} + \frac{1}{2}\beta_i \sum_{l \in S} \sum_{l' \in S, l' \neq l} \tau(l, l') \tag{1}$$

where $V_i(S)$ represents bidder i's valuation for license set S and β_i is the complementarity parameter by bidder type, which denotes the valuation of one unit of the complementarity index. We allow different types of bidders to have different values for this parameter, and it is one of the key structural parameters to be estimated.

Every bidder forms a belief about winning a license l in round t. We allow this belief to depend on the provisional winning set for the bidder in the previous round, W_{it-1}, the number of active bidders competing for the license in that round, and also bidder-license specific characteristics. The belief of winning a particular license is also dependent on the bidding set of bidder i in round t. We assume that the bidders bid straightforwardly without any jump bidding, where the bidders decide whether to enter or not for a circle by round three. We observe that 88% of all bidder entries for licenses they ever bid on occur before round 3. Further there were only 12 distinct rounds where new entries took place after round three (Figure A1) and choose to bid on any particular license if it is not in the provisional winning set W_{it-1} for the previous round.

Thus, the probability of winning any license l is assumed to be 0 if in any round t license l is neither in the bidding set B_{it} nor in the provisional winning set for the previous round W_{it-1}. The probability of winning a license is allowed to be non zero and different for any round t, conditional on whether the license is in the bidding set B_{it} or in the provisional winning set for the previous round W_{it-1}. The belief of bidder i winning any license l in clockround t is $Pr_{it}(l|B_{it}, W_{it-1})$. In this paper, this probability will also be denoted by $Pr_{it}(l)$ for notational brevity where required.

We adopt the Bayesian Nash Equilibrium (BNE) concept and the corresponding model assumptions used in Xiao and Yuan (2022b) where bidders adopt strategies and beliefs in every round. The strategy $\sigma_{it}(v_i, \beta_i, P_t, Pr_{it})$ for each bidder i in round t is a binary decision regarding whether to bid or not bid in every circle l and is a function of the vector of standalone valuations for all licenses $v_i = \{v_{il}\}_{l\in\mathcal{L}}$, the complementarity parameter β_i, license-round level prices $P_t = \{P_{lt}\}_{l\in\mathcal{L}}$, and their belief of winning $Pr_{it}(.) = \{Pr_{it}(l)\}_{l\in\mathcal{L}}$.

The BNE comprises of strategies $\sigma_i^*(.) = \{\sigma_{it}^*(.), t = 4, ..., T\}$ and beliefs $Pr_i^*(.) = \{Pr_{it}^*(.), t = 4, ..., T\}$ such that for each bidder i of type $\{v_i, \beta_i\}$ in round t, the strategy σ_{it}^* maximizes expected profit given beliefs Pr_{it}^* as follows

$$\begin{aligned}\sigma_{it}^*(v_i, \beta_i, P_t, Pr_{it}) = \\ & argmax_{B_{it}}\Bigg\{\sum_{l\in S} v_{il}\, Pr_{it}^*(l|B_{it}, W_{it-1}) + \frac{1}{2}\beta_i \sum_{l,l'} \tau(l,l')\, Pr_{it}^*(l,l'|B_{it}, W_{it-1}) \\ & - \sum_{l} P_{lt}\, Pr_{it}^*(l|B_{it}, W_{it-1})\Bigg\}\end{aligned} \tag{2}$$

and the beliefs $Pr_i^*(.)$ are consistent with the equilibrium strategies $\sigma_i^*(.)$ such that each players strategy is optimal given their beliefs, and the beliefs are derived from these strategies. Additionally, we assume the following :

1. **Assumption 1:** The probabilities of winning two licenses are independent of each other, conditional on B_{it}, W_{it-1}.

Thus $Pr(l, l'|B_{it}, W_{it-1}) = Pr(l|B_{it}, W_{it-1}) \times Pr(l'|B_{it}, W_{it-1})$ in equation 2

2. **Assumption 2:** Each bidder i believes the current round to be the final round and $Pr(l|B_{it}, W_{it-1}) = 0$ if $l \notin W_{it-1} \cup B_{it}$

The expected profit in equation 2 consists of two components. The first term on the right-hand side represents the bidders expected valuation across all licenses under their beliefs, while the second term captures the expected cost, determined by the prevailing clock-round prices under Assumptions 1 and 2.

We identify and estimate the model primitives of our framework, which includes the complementarity parameter β_i, which we allow to vary by bidder types, the equilibrium beliefs $Pr_{it}(l)$, and the fundamentals of the distribution of the private value v_{il}. Our identification strategy exploits round-to-round variation in bidding behavior to separately identify complementarity effects and standalone values. The identification process proceeds in two steps:

1. When a bidder changes their bidding decision on a specific license between rounds without price changes on that license, this reveals information about their complementarity valuation.

2. Differences in bidding patterns across licenses and rounds with varying market characteristics identify the determinants of standalone license values.

The identification and estimation of these will be discussed in the next section.

5 Identification and Estimation

5.1 Specification of the Complementarity Index

This subsection describes the construction of the complementarity index, $\tau(l, l')$. We follow the travel-based complementarity index developed by Fox and Bajari (2013), who use airline passenger flows to measure complementarities across geographic markets in the U.S. context. In our setting, airplane trips are replaced by the number of unique trains connecting two regions, which provides a more contextually appropriate measure of economic integration in India. A key innovation in our application is the construction of a complementarity measure that reflects patterns of economic integration specific to the Indian context.

Traditional measures of complementarities often rely on geographic distance or population-weighted distances between markets (see Fox and Bajari (2013)). While convenient, such measures are limited because geographic proximity does not necessarily correspond to the intensity of actual travel, trade, or business interactions across regions. Similarly, an airline-travelbased index, though effective in the U.S. context, is less suitable for developing countries such as India in 2010. At that time, air travel remained relatively expensive and concentrated in a few metropolitan hubs, serving only a small share of the population. As a result, airline connectivity fails to capture the broader patterns of mobility and economic integration across regions that are more accurately reflected in Indias extensive railway network.

Our train-based complementarity index provides a novel alternative. By exploiting Indias extensive railway network, it captures both passenger and business travel flows between service areas. This makes the index a more meaningful proxy for roaming demand and network value complementarities that drive spectrum license synergies in auctions. Finally, the strong correlation between train connectivity and observed bidding clusters provides empirical validation of this approach. It suggests that measures of actual travel and connectivity, as opposed to purely geographic distance, may be broadly applicable to the study of spectrum auctions and other markets in developing country contexts.

Bidder behavior is suggestive of complementarities. In Figure 3b we can observe significant geographical clustering of winnings for Aircel and Idea which won mostly adjacent licenses. However, Vodafone's geographically scattered winnings suggest existence of complementarities beyond geographic, if they exist. To explore this issue, we construct index based on train connectivity.

Train Complementarity Index

We construct a travel-based complementarity index with the number of unique trains connecting two regions. This measure is then adapted to yield a pairwise complementarity index, expressed in MHz, between any two licenses l and l' given by,

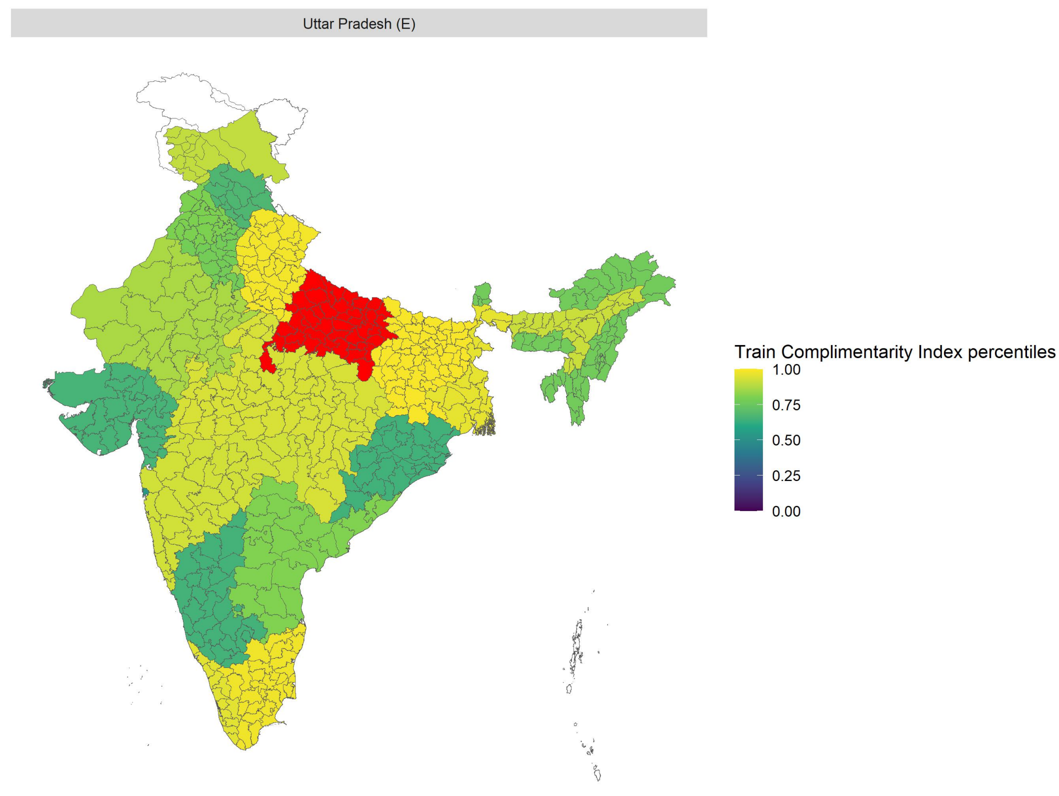
$$\tau(l, l') = \text{MHzBand} * \left(pop_l * \frac{Trains_{l,l'}}{\sum_{j \in L \setminus \{l\}} Trains_{l,j}} + pop_{l'} * \frac{Trains_{l',l}}{\sum_{j \in L \setminus \{l'\}} Trains_{l',j}} \right) \tag{3}$$

where pop_l represents the fraction of the India's population living in license area l; L denotes set of all licenses sold at the auction; $Trains_{l,l'}$ refers to all the unique trains that have a stop at stations within license area l' after having visited a station in license area l ; and MHzBand refers to the Frequency Band of the sold licenses, which was fixed at 2100 MHz.

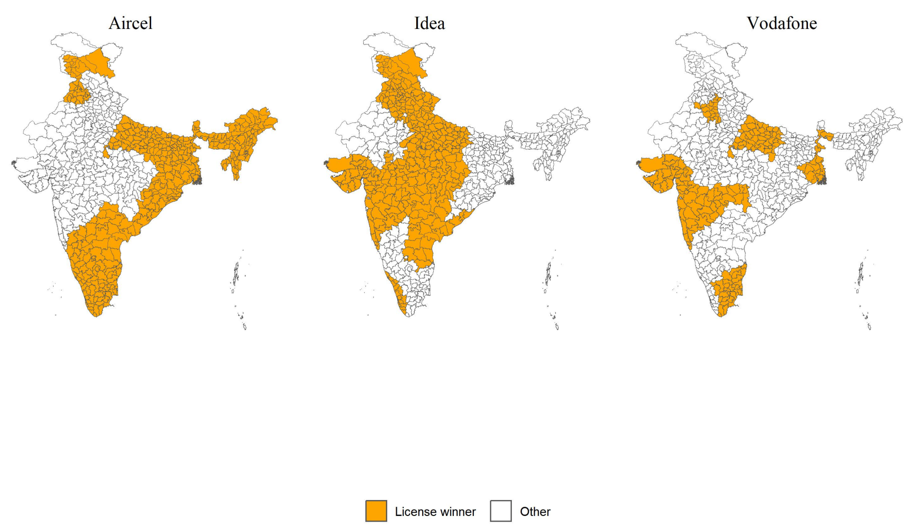
Figure 3a illustrates the pairwise complementarity index percentiles for the Eastern Uttar Pradesh (UPE) license area with all other license areas. Unsurprisingly, we can see that the index correlates significantly with geographic proximity. However, it also captures information beyond geographical distance and population size, which we believe to be information on cultural and economic ties between circles. In particular, we can observe that the value of the UPE index with Tamil Nadu, located in the southern part of the country and geographically distant, is noticeably high. The geographical location of other circles won by operators who also won UPE, as shown in Figure 3b, closely correlates with the geographical distribution of its complementarity index. These operators not only tend to win in the neighboring circles, but also 2 out of 3 winners of UPE (Aircel and Vodafone) also won Tamil Nadu. This is even more striking in the case of Vodafone, where this correlation is not evident based on the geographical proximity.

5.2 Identification of the Complementarity Parameter β_i

Equation 2 gives us the equilibrium bidding strategy for each bidder i in round t. As discussed in Section 4, the strategy space is large, as each bidder optimally chooses whether or not to bid in



(a) Complementarity Index in percentiles for Uttar Pradesh (E)



(b) Other Licenses won by Uttar Pradesh (E) winners

Figure 3: Complementarity patterns and outcomes: (a) shows the index in percentiles for Uttar Pradesh (E), with the circle itself marked in red. The map shows that the complementarity index captures both geographical proximity and cultural proximity, as shown by the relatively high index between UP (E) and circles like Tamil Nadu. (b) shows license-winning patterns for service providers who won UP (E), closely reflecting the complementarity index pattern.

all possible licenses in every round. Instead of characterizing the equilibrium, we use a revealed preference approach for identifying the complementarity index β_i. Under the given framework and the model assumptions, we can single out the incremental value each license l adds to a bidder as $v_{il}+\beta_i \sum_{l'} \tau(l,l')Pr_{it}(l')$ where v_{il} is the standalone value of the license and $\sum_{l'} \tau(l,l')Pr_{it}(l')$ is the expected marginal complementarity that license l adds to all other licenses under the bidders' belief.

Assumption 3: We assume that in every round a bidder bids for a license l, the expected marginal benefit should be greater than or equal to the expected cost of acquiring the license in that round. Conversely, when a bidder does not bid for a license when it is eligible to do so and is not a provisional winner in that license, the opposite holds true.

Under the given assumptions, and the expected profit function, the following inequalities hold true:

$$v_{il} + \beta_i \sum_{l'} \tau(l,l')Pr_{it}(l') \geq P_{lt} \quad \text{if} \quad l \in B_{it} \tag{4}$$

and when i is eligible to bid for l in round t'

$$v_{il} + \beta_i \sum_{l'} \tau(l,l')Pr_{it'}(l') \leq P_{lt'} \quad \text{if} \quad l \notin B_{it'} \cup W_{it'-1} \tag{5}$$

Bidders revealed preference conditions generate bounds on the complementarity coefficient β_i. If license l is included in the bid set at round t, its marginal contribution must exceed the posted price; If it is excluded, the marginal contribution must be no greater than the price. These two cases lead to the following moment inequality after differencing across rounds t and t':

$$\beta_i \sum_{l'} \tau(l,l')[Pr_{it}(l') - Pr_{it'}(l')] - (P_{lt} - P_{lt'}) \ \geq \ 0, \tag{6}$$

We define $\Delta Comp_i(l,t,t') = \sum_{l'} \tau(l,l')[Pr_{it}(l') - Pr_{it'}(l')]$ as the expected difference in the marginal complementarity of license l to bidder i between two rounds t and t'. In the data, we observe bidder behavior across licenses and over rounds, which are used to identify β_i.

Consider a simple hypothetical illustration using bidder i bidding for license l. In round 24, when the standing price was INR 500 million, bidder i submitted a bid. In round 25, however, at the higher price of INR 520 million and with no change in its other holdings, bidder i chose not to bid on l. These observed choices imply the following revealed-preference inequalities:

$$\begin{aligned} &\text{Round 24:} \qquad v_{il} + \beta_i \cdot \mathbb{E}[\text{Comp}_{24}] \ \geq \ 500\text{M}, \\ &\text{Round 25:} \qquad v_{il} + \beta_i \cdot \mathbb{E}[\text{Comp}_{25}] \ \leq \ 520\text{M}, \end{aligned}$$

where $\mathbb{E}[\text{Comp}_t]$ denotes the expected marginal complementarity of license l for bidder i in round t, expressed in INR terms via multiplication by β_i. Differencing across rounds eliminates the standalone value v_{il} and yields an upper bound on the complementarity coefficient (when $\mathbb{E}[\text{Comp}_{25}] - \mathbb{E}[\text{Comp}_{24}] > 0$):

$$\beta_i \ \leq \ \frac{20\text{M}}{\Delta Comp_i(l,25,24)}.$$

Similarly, the lower bound for β_i can be constructed using two rounds t where the bidder does not bid and t' where the bidder starts bidding on that license and $P_{lt} < P_{lt'}$. However, in order to construct the required inequalities given by equation 6, we need the belief of each bidder-round-license specific beliefs, which we proceed to estimate in the next section.

5.3 Belief Estimation

We estimate bidders' beliefs about winning probabilities using a probit model that captures how market participants form expectations in the dynamic auction environment. We model belief formation as a function of observable auction characteristics, competitive environment, and license-specific attributes. The estimation employs a parametric specification where bidder i's belief about winning license l in round t is given by $Pr_{it}(l|W_{it-1}, B_{it}) = \Phi(\mathbf{X}_{ilt}\boldsymbol{\alpha})$, where $\Phi(\cdot)$ represents the standard normal cumulative distribution function and $\mathbf{X}_{ilt}$ contains relevant explanatory variables. Following Assumption 1, we estimate the probabilities of winning each license separately. Following Assumption 2, we set the probability of winning a license in a given round to be zero if the bidder does not bid on the license and the license is not in the bidder's provisional winning set. Given the model assumptions, we estimate separate models for two distinct scenarios: when bidders are actively placing bids and when they hold provisional winner status from previous rounds. This approach recognizes that belief formation processes may differ between aggressive bidding situations and defensive positions where bidders must decide whether to continue competing. The model of bidder belief incorporates the competition intensity and other license-bidder characteristics that affect the level of competition for a license, like incumbent status of the bidder, license attributes like population and the level of urbanization, infrastructure variables captured by tower density, and crucially, complementarity measures that capture synergies with bidders' existing spectrums where it is a provisional winner. The beliefs also depend on the clock round number in question as the probability of winning the license potentially increases as the SMRA auction progresses.

5.4 Belief Estimation Results

The estimation results presented in Table 1 reveal systematic patterns in how bidders form winning expectations during Indian spectrum auctions. The table reports the average marginal effects and also the estimated parameters for the logit model. Competition intensity exhibits the expected negative relationship with winning beliefs. When three, four, or more than five competitors are active in bidding for a license in a given clock round, the probability of winning decreases by 0.23, 0.317, and 0.31, respectively, indicating that bidders rationally scale back their expectations as competition intensifies. However, this reduction in belief regarding winning the license with increased competition from other bidders is much lower when an operator is already a provisional winner in a circle. Incumbent operators display significantly higher confidence levels, reflecting their strategic advantages through existing market presence, spectrum holdings, and superior information about market conditions. The substantial confidence enjoyed by incumbent operators highlights the persistent advantages of established market players in spectrum acquisition, raising essential policy questions about market concentration and competitive dynamics in the Indian telecommunications sector.

Table 1: Belief Estimation Results

Variable	**Bid (Coef.)**	**Bid (AME)**	**Prov. Winner (Coef.)**	**Prov. Winner (AME)**
Round	0.00449***	0.00160***	0.00254***	0.00081***
	(0.00034)	(0.00011)	(0.00032)	(0.00010)
3 Competitors	-0.669***	-0.23841***	-0.133***	-0.04235***
	(0.0846)	(0.02980)	(0.0354)	(0.01123)
4 Competitors	-0.889***	-0.31702***	-0.465***	-0.14790***
	(0.0813)	(0.02825)	(0.0424)	(0.01327)
>5 Competitors	-0.872***	-0.31087***	-0.433***	-0.13759***
	(0.0811)	(0.02820)	(0.0494)	(0.01554)
Incumbent	0.716***	0.25530***	1.240***	0.39391***
	(0.0929)	(0.03266)	(0.0570)	(0.01698)
Population share (%)	-0.0502***	-0.01790***	-0.077***	-0.02468***
	(0.01)	(0.00355)	(0.0072)	(0.00229)
Urbanratio	-0.911***	-0.32471***	-1.888***	-0.59995***
	(0.1634)	(0.05781)	(0.1408)	(0.04372)
ln(Population Density)	-0.098	-0.03505	0.215**	0.06843**
	(0.1500)	(0.05346)	(0.0791)	(0.02511)
ln(Tower Density)	0.150	0.05337	-0.018	-0.00574
	(0.1137)	(0.04054)	(0.0621)	(0.01972)
Complementarity	0.00214***	0.00036***	0.00091***	0.00008*
	(0.00025)	(0.000047)	(0.00023)	(0.000037)
Complementarity^2	-1.919e-06***		-1.047e-06***	
	(0.00000)		(0.00000)	

Notes: This table presents belief estimation results using bid and provisional winner outcomes. The table reports both the coefficient estimates and the average marginal effects for both specifications. The observations are at the circle-bidder-round level. Standard errors are in parentheses. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Complementarity effects follow an inverted U-shaped pattern, suggesting that spectrum synergies initially enhance winning probabilities, but this effect diminishes at higher complementarity levels, possibly due to increased competition for highly synergistic license combinations as they seek to expand their coverage areas. The complementarity patterns suggest strategic thinking, where bidders recognize spectrum synergies but also anticipate that competitors will similarly value complementary combinations, leading to more competitive bidding environments as operators try to create license packages covering larger geographical areas with increased synergies. This is evident in the auction outcomes, as none of the bidders could win an all-India level license and were primarily restricted to certain geographical areas, serving as their stronghold. The temporal dimension shows positive round coefficients, indicating that bidders become more confident as auctions progress and market information is revealed through the bidding process.

The belief estimation results also provide important insights into the strategic behavior and market dynamics characterizing Indian spectrum auctions. The strong negative coefficients on population share expressed as the percentage of the national population in the circle and urbanization ratio reveal that bidders express lower confidence in more valuable markets, suggesting that these circles attract disproportionately intense competition that outweighs their underlying value advantages. This finding aligns with the revenue maximization objectives of spectrum auctions, where high-value licenses generate fierce bidding competition that makes individual bidders more pessimistic about their winning chances. Controlling for other license characteristics, existing telecom infrastructure in terms of tower density does not significantly increase the belief of bidders regarding winning a license, though point estimates show a positive average marginal effect on the probability of winning. These belief formation patterns have significant implications for auction design and policy, as they demonstrate how market structure, bidder characteristics, and license attributes interact to shape competitive dynamics and ultimately influence spectrum allocation efficiency in the Indian context.

5.5 Complementarity Estimates

We use equation 6 derived from the bidders' revealed preferences for estimating the complementarity parameters β_i by converting them to a set of moment inequalities under suitable restrictions on the prediction errors coming from the belief estimation in the previous section. We replace the winning probability beliefs in equation 6 with the predicted probabilities using parameters of Table 1. Replacing The true probabilities with the estimated probabilities $\hat{P}r_{it}(l)$, we get

$$\beta_i \sum_{l'} \tau(l, l')[\hat{P}r_{it}(l') - \hat{P}r_{it'}(l')] - (P_{lt} - P_{lt'}) + (\epsilon_{ilt} - \epsilon_{ilt'}) \geq 0,$$

where ϵ_{ilt} is the error in predicting the complementarity values under the estimated probabilities. Using suitable non-negative instruments Z that satisfy $E[\epsilon_{ilt}|z] = 0$, we can derive the unconditional moment inequality given by

$$E\Big[z\big[\beta_i \Delta \widehat{\text{Comp}}_i(l, t, t') - (P_{lt} - P_{lt'})\big]\Big] \geq 0 \tag{7}$$

where $\Delta \widehat{\text{Comp}}_i(l, t, t')$ is the predicted expected difference in the marginal complementarity of

license l to bidder i between two rounds l and l' under the predicted probabilities. We follow Xiao and Yuan (2022b) to assume that conditional on the predicted expected marginal complementarity and the bid of a bidder i in round t for license l, the errors in calculating the expected marginal complementarity valuation of a license using estimated belief are mean zero, which implies that
Assumption 4: $E[\epsilon_{ilt} | \sum_{l'} \tau(l,l')\hat{P}r_{it}(l'), B_{ilt}] = 0$

We follow Andrews and Shi (2013) to create non negative instruments using quantiles of $\Delta Comp_i(l,t,t')$, where $z(\Delta Comp_i(l,t,t'))$ is an indicator variable taking one if the corresponding expected marginal complementarity belongs to a particular quantile and zero otherwise. Using the instruments, the corresponding criterion function is used to estimate the complementarity parameter

$$Q(\beta_i) = \sum_{z(\widehat{\text{Comp}}_i(l,t,t'))} min\left\{ z(\widehat{\text{Comp}}_i(l,t,t')) \times \left[\beta_i \Delta \widehat{\text{Comp}}_i(l,t,t') - (P_{lt} - P_{lt'})\right], 0 \right\}$$

Table 2 presents our main complementarity estimates by bidder category. We find substantial complementarity effects with a non-monotonic relationship across bidder sizes that replicates patterns in existing literature in other developed markets.

Table 2: Complementarity Parameter Estimates

Bidder Category	β_i (INR 10 Million)	95% Confidence Interval
Combined	1.5033	[1.4690, 1.5411]
Large Bidders	2.4660	[2.4014, 2.5333]
Medium & Small Bidders	0.8931	[0.8680, 0.9167]

Note: Large bidders include Bharti, Vodafone, and Reliance Communications. Medium & Small bidders include the rest, like Idea Cellular, Aircel, and Etisalat, etc. Combined pools all bidders. Estimates are based on bidder-license-round level data

Large bidders like Bharti Airtel, Reliance Communications exhibit the highest complementarity at INR 24.6 million per MHz, reflecting economies of scope from existing network infrastructure and the ability to realize synergies across service areas. Medium and small bidders show significant complementarity of INR 8.93 million per MHz driven by arbitrage opportunities and potential for resale to large operators.[4] Our estimate of β_i yields a 95% confidence interval for the all-India licenses complementarity value, with lower and upper bounds of 30.85 and 32.36 INR billion, respectively.

Our estimates show that complementarity effects are strong in our institutional setting and the incentives of large bidders to win license packages covering large geographical areas and sharing reasonably high complementarity. Medium and small bidders, on the other hand, won fewer licenses, often in geographically proximate circles or in isolated markets. The lower estimated

[4] Separating bidders into three categories, large, medium, and small, shows a non-monotonic patternLarge > Small > Medium and demonstrates the robustness of this relationship across different institutional contexts when compared to earlier studies in different markets. However, we combine medium and small bidders into one category due to the small number of bid data for small firms compared to the other groups.

complementarity parameter reflects that these operators have limited incentives to assemble large, contiguous service areas. Higher operational and scaling costs make nationwide expansion less attractive, so their strategies focus instead on consolidating existing strongholds where they already have market presence. These estimated structural parameters, β_i, will play a crucial role in our simulations, enabling us to capture bidder behavior across rounds, given their observed auction history in counterfactual scenarios.

5.6 Stand-alone Values

We parameterize the mean stand-alone valuation of each bidder for a cirlce as

$$v_{il} = X_{il}\theta + \xi_{il} \tag{8}$$

where X_{il} captures both circle level and bidder level characteristics and ξ_{il} is the unobserved private valuation. In out likelihood estimation we assume $\xi_{il} \sim \mathcal{N}(0, \sigma^2)$ and independent across bidder-licenses.

The set of circle-level characteristics that are used to capture the observed component of the stand-alone valuation is the total population of the circle, the log of the population density, the log of the tower density, and the share of urban population. The stand-alone valuations are allowed to depend on the quality of service and the nature of incumbency of the bidders by including the market shares and their interaction with the percentage of BTS downtime and good voice quality for the bidder in the circle. We also include the bidder level means of the BTS downtime and the good voice quality percentages across all the circles where they are active as a measure of bidder level service quality.

The probability that a bidder i will bid for a circle l in round t can be written as follows using the distributional assumption on the private value component ξ_{il}:

$$Pr(Bid_{ilt} = 1|\cdot) = \Phi((X_{il}\theta + \hat{\beta}_i \sum_{l'} \tau(l, l')\hat{P}r(l') - P_{lt})/\sigma)$$

This probability is used to construct the log-likelihood function and use the observed data on the bidding choices of the firms for service areas across rounds to estimate the set of parameters $\{\theta, \sigma^2\}$.

The results of the log likelihood estimates of the parameters of the stand-alone valuation is provided in Table 3. The stand-alone valuation of a circle significantly increases with improved infrastructure, as suggested by the coefficient estimates for the log of tower density and the share of urban population. However, controlling for the urban ratio, an increase in total population and population density is observed to be associated with a mildly significant decrease in the valuation of the circle that can be due to increased cost of infrastructural improvement in demographically dense regions.

Market share captures the the extent of a bidders incumbency within a circle and significantly increases the valuation of the bidder for a circle. A strong positive effect of the interaction between

Table 3: Log-Likelihood Estimates of Stand-alone Valuation Parameters (INR Billion)

Variable	**Estimate**
Intercept	-0.117
	(0.462)
Population share	-0.267**
	(0.155)
Log Tower Density	2.686***
	(0.637)
Log Population Density	-2.624*
	(1.363)
Urban Population Share	5.675**
	(2.401)
Market Share	13.656***
	(5.105)
Market Share × BTS Downtime	-0.004
	(0.005)
Market Share × Good Voice Quality	10.811***
	(3.759)
Mean BTS Downtime (bidder)	-0.499**
	(0.196)
Mean Good Voice Quality (bidder)	0.380
	(0.272)
Standard Deviation (σ)	14.539***
	(1.789)

Notes: This table reports point estimates and bootstrapped standard errors (in parentheses) from the log-likelihood estimation of the stand-alone valuation model. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

the market shares and the percentage of good voice quality implies that better service quality substantially increases the marginal standalone valuations from increased market presence in a circle. Also, bidders with lower service quality on average, as measured by the mean BTS Downtime, have reduced valuation.

We use the loglikelihood estimates provided in Table 3 to construct the predicted stand-alone valuation for a bidder-license pair using observed covariates as $\hat{v}_{il} = X_{il}\hat{\theta}$. We construct the predicted valuations for the state owned companies BSNL and MTNL along with the observed bidders. These predicted stand-alone valuations $\hat{v}_{il}$, the estimated complementarity parameter $\hat{\beta}_i$, and the complementarity index, along with the predicted beliefs, will be used in our counterfactual simulation provided in the next section.

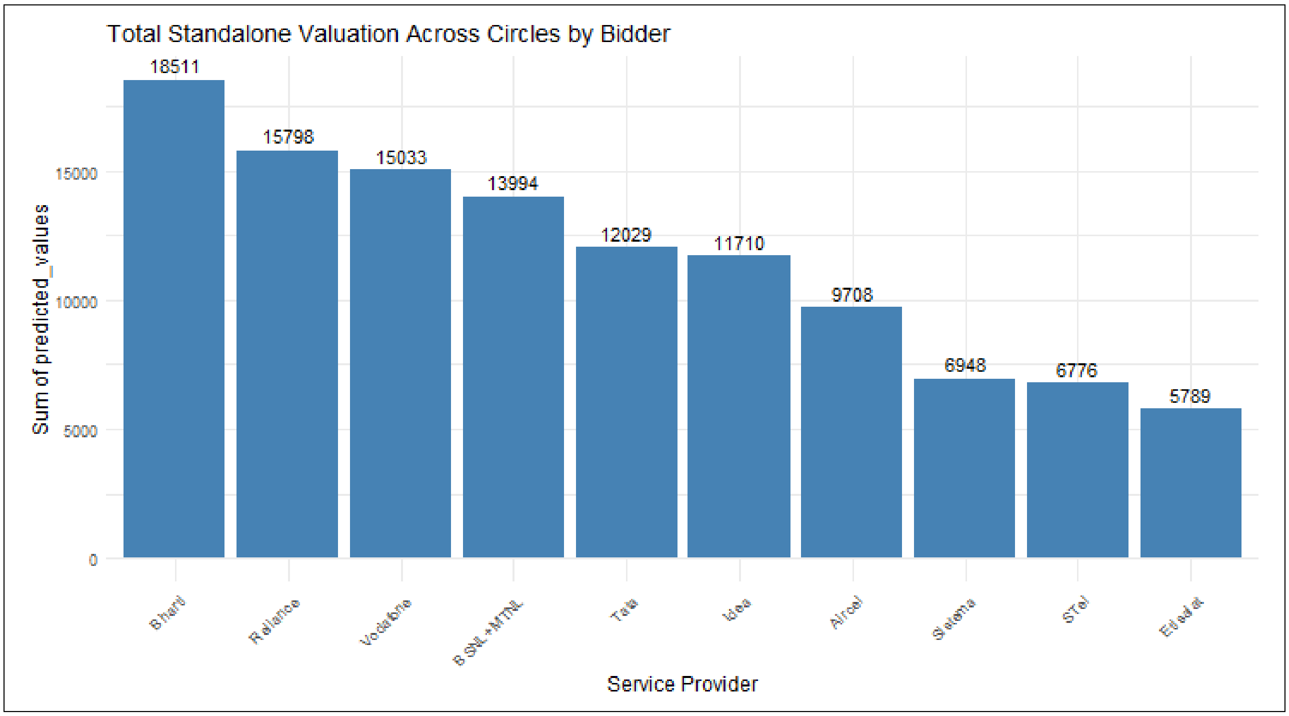


Figure 4: Bar plot showing the total predicted stand-alone valuation of service providers across all circles in India in INR 10 million. Only service providers included in the counterfactual bidding are shown. The Y-axis represents the sum of predicted valuations across all circles for each provider, while the X-axis lists the names of individual service providers. MTNL includes only Delhi and Mumbai, and BSNL excludes these two circles. Their combined total is shown as "BSNL+MTNL" to reflect aggregate valuation across their respective operational areas.

5.7 BSNL Performance Analysis

Figure 4 shows the sum of the predicted stand-alone valuations of each bidder across all circles of India in INR 10 million. The predicted all-India level stand-alone valuation for the public service providers is given by BSNL+MTNL due to the reason stated previously. We observe that service providers like Bharti, Reliance, and Vodafone have a higher predicted stand-alone valuation. Low predicted value of service providers like Stel and Siestema can be corroborated by the fact that these are mostly regional players. The total predicted valuation of public service providers rank fourth and this has important consequences for our counterfactual. The status quo set aside mechanism is thus reducing competition from a relatively high valued bidder from the spectrum auction, and our counterfactual will analyze the effect of having them participate in the auctions. Interestingly, as of 2025, only four service providers are operating in India, and three of them are from our predicted four highest valuing service providers.[5]

Table 4: BSNL's Rank by Service Area

Service Area	**Rank**
Himachal Pradesh	2
Haryana	2
North East	2
Punjab	2
Bihar	3
Jammu and Kashmir	3
Kerala	3
Orissa	3
Assam	4
Madhya Pradesh	4
Rajasthan	4
Uttar Pradesh (E)	4
West Bengal	4
Mumbai	5
Gujarat	5
Karnataka	5
Kolkata	5
Tamil Nadu	5
Uttar Pradesh (W)	5
Delhi	6
Andhra Pradesh	6
Maharashtra	6

Notes: The table presents BSNL's (and MTNL's, where applicable) rank in terms of the predicted mean stand-alone valuation for each service area. Service areas are ordered from highest to lowest ranked.

We look at BSNL's ranking in terms of the predicted mean stand-alone valuation with respect to other private service providers for all service areas in Table 4. As earlier, we look at MTNL's ranking for service areas, Delhi and Mumbai and BSNL for all other circles. BSNL tends to have a higher ranking in northern and northeastern hilly regions such as Himachal Pradesh, Jammu and Kashmir, and the North East, as well as in predominantly rural eastern regions like Bihar, Assam, and Orissa, and the northwestern plains of Punjab and Haryana.The predicted ranking is weaker for BSNL in most southern states and urban centers, such as Kolkata, Delhi, and Mumbai. We will observe similar patterns emerging in our counterfactual, although not perfectly reflecting this ranking, due to the complementarities among these circles entering the valuation of license bundles,

[5]The existing service providers are Bharti, Vodafone, BSNL, and Reliance Jio who entered the market in 2016.

which will influence the bidding behavior of the participants.

6 Counterfactual Simulation

In our counterfactual analysis, we examine the impact of having the public operator BSNL participate in the auction. We will refer to the public operators as BSNL in this section. Using our counterfactual simulations, we primarily explore the effect on government revenue and its tradeoff with the universal service obligation measured in terms of the expected share of the national population with access to the public operator's service. We use the estimated structural parameters for our counterfactual analysis. Given the bidder license valuations and the complementarity parameters, we simulate the outcome of the SMRA auction where our algorithm computes a minimum bidding set for each bidder in every round, which consists of those licenses in which the bidder will always bid in the round, given the history. The algorithm proceeds over rounds until the SMRA stopping rules are satisfied and no new bids are received for any service area. The algorithm we use is as follows:

Minimum Bidding Set Algorithm

1. Simulation begins from round $t = 3$ where bidder i bids for a specific service area l if it is ever observed to bid for that license in the data. BSNL is assumed to bid for all the licenses in this first round

2. For any round $t > 3$ a set of provisional winning set of bidder i given by W_{it-1}

3. for every round t compute the minimum bidding set iteratively as:

   - Initialize with empty set: $\boldsymbol{B}_{it}^{(0)} = \emptyset$
   - In every iteration $k \geq 1$ for each license not in the set $W_{i,t-1} \cup \boldsymbol{B}_{it}^{(k-1)}$, compute marginal value:
   $$\text{Marginal Value}_{il} = v_{il} + \beta_i \sum_{l' \in W_{i,t-1} \cup \boldsymbol{B}_i^{(k-1)}} \tau(l, l') \cdot \mathbb{P}_{it}(l') \tag{9}$$
   - Add license to $\boldsymbol{B}_{it}^{(k)}$ if marginal value exceeds round price for the license
   - Continue until no new licenses are added for any bidder to their minimum bidding set $\boldsymbol{B}_{it}$

4. If the number of bids for a license exceeds the possible winners in any service area, choose a set of provisional winners for the service area in that round randomly, where the number of provisional winners for a service area is equal to the total spectrum to be allocated there.

5. Iterate until no new bids are received for any service area

We simulate both the benchmark and the counterfactual auction outcomes using the structural parameters used in the previous sections. We perform 200 simulations of both the benchmark and the counterfactual auctions. The mean stand-alone valuations for a firm-circle pair are constructed using parameter estimates in Table 3. For every simulation, the private valuations ξ_{il} are drawn from a truncated standard normal distribution and added to the mean stand-alone valuations for the firm-bidder value. In order to avoid draws of extreme values of ξ_{il}, we use a truncated normal distribution, where the bounds are provided by equations (4) and (5), depending on whether the bidders bid for a license or not in a round, respectively. The public service provider operates under the name MTNL in two bid cities, Delhi and Mumbai, and as BSNL everywhere else. In the counterfactual simulation, we put the two public service providers under one category and will be together called BSNL, where the valuations of MTNL are used for Delhi and Mumbai circles, and BSNL for the rest of the circles based on their area of operations. We assume that the two public sector service providers act as a single bidding unit in our counterfactual.[6]

6.1 Simulation Results

We initialize from round three, and any bidder who has ever bid for a particular circle is part of the initial set of bidders for that circle. We first simulate our model for the benchmark case to mimic the status quo using the minimum bidding set algorithm described in the previous subsection to verify the accuracy of our model. In the benchmark case, BSNL is not considered as a participant in the auctions, and one spectrum block in every service area is set aside. We report the distribution of the all-India price across all 200 simulations in Figure 5 and compare it with the observed price of 17167.61 crore rupees in our data. The all-India price that we report is the sum of prices across all circles. The mean all-India price in the benchmark simulations is 17311.03 crore rupees, which is very close to the observed price, with a difference of less than 1%, suggesting that our model simulation performs well to predict the status quo outcome.

In the counterfactual simulation, we include BSNL in the initial bidder set for all circles and increase the number of potential winners by one to ensure that the total number of service providers in a circle remains constant. This initialization is done keeping in mind that the government service providers operate in all circles. The distribution of the all-India price across simulations is reported in Figure 5, and we observe a rightward shift compared to the benchmark distribution. The mean all-India price in the counterfactual simulation is 19354.73 crore rupees, which is an 11.8% increase over the mean of the benchmark simulation and similarly a 12.7% increase over the observed all-India price. The counterfactual also shows a 7% increase in the mean national revenue when compared to the same for the status quo benchmark simulation and a 7.6% increase when compared to the observed national revenue (Figure A2). A KolmogorovSmirnov test indicates that the benchmark and counterfactual distributions are significantly different (p-value < 2.2e-16).

[6]Both were public sector undertakings (PSUs) owned by the Government of India under the Department of Telecommunications (DoT). In 2010, they had distinct boards of directors, CMDs (Chairman and Managing Directors), and operational structures. However, there have been and increasingly more in recent years, more integration in operations and strategy.

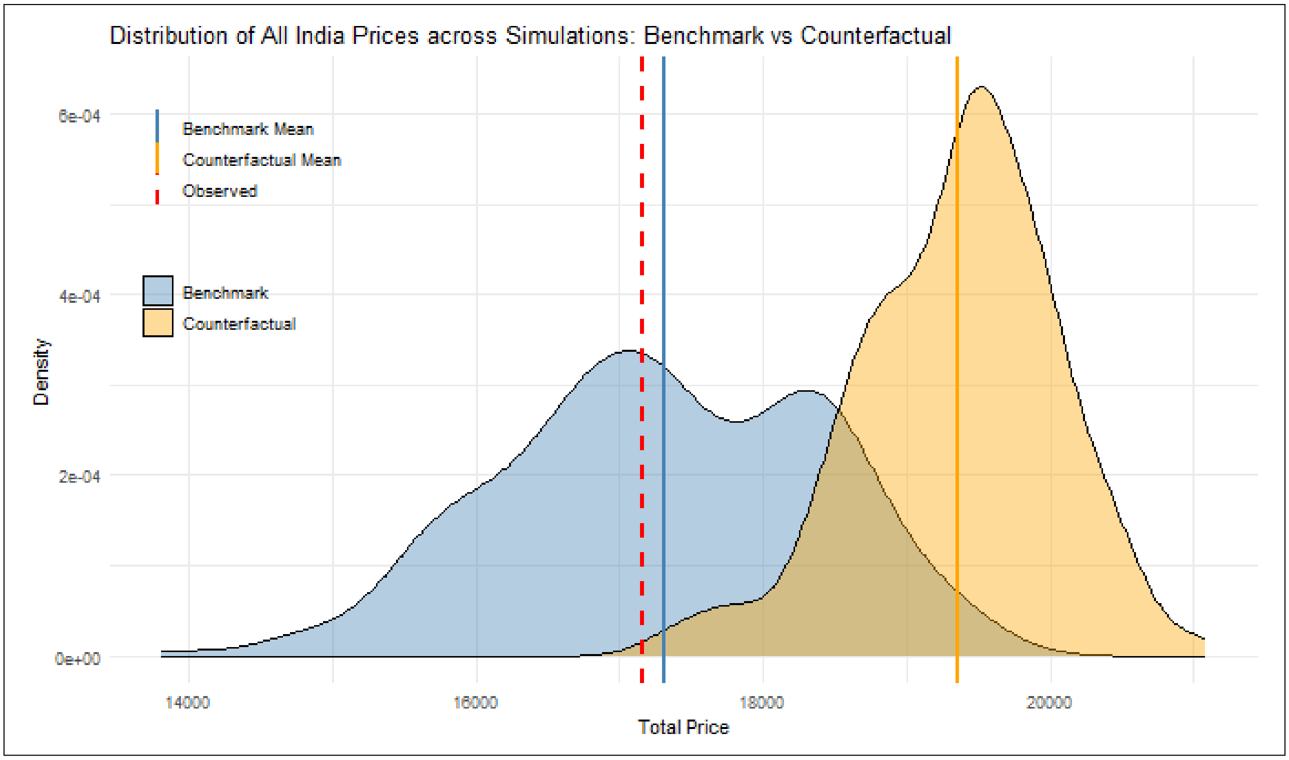


Figure 5: Distribution of all India spectrum price for the benchmark and the counterfactual simulations. The distribution of the benchmark simulation is shown in blue, with the mean of the distribution marked with a vertical line of the same color. The red dashed line marks the observed all-India price, which is close to the mean of the benchmark simulation. The counterfactual distribution and the mean all-India price are shown in yellow. The distribution shifts right and is less dispersed in the counterfactual.

We analyze the outcomes of our counterfactual simulation to identify which circles drive the observed increase in auction prices. The results reveal substantial heterogeneity across circles, both in the final winning prices and in the probability of BSNL winning them. To explore this relationship, Figure 7 plots the difference between average counterfactual and benchmark simulation prices for each circle against BSNLs simulated win probability, which reveals an almost inverted U-shaped pattern. Circles where BSNLs win probability is below 0.5 tend to show negligible or negative price differences. The negative changes likely reflect reduced competition when an additional potential winner is introduced in the counterfactual. At the other extreme, in circles where BSNLs win probability approaches one, the impact on final prices is also minimal, as BSNLs dominance seems to dampen competitive pressure. The largest positive price effects emerge in circles where BSNLs win probability lies between 0.65 and 0.9. We explain this observed pattern by exploring BSNL's predicted standalone values across circles, the spatial distribution of these standalone values, and the complementarities between licenses.

Circles with Probability of BSNL winning is less than 0.5: We observe that BSNL performs poorly in circles that are located in the southern and western parts of the country, as shown in Figure 7. In all the circles except Kerala in this region, BSNL also has a relatively low standing in terms of its mean stand-alone valuations as given in Table 4. In circles like Gujarat and Maharashtra, the probability of winning is as low as 0.02 and 0.07, respectively. Most of these circles saw intense

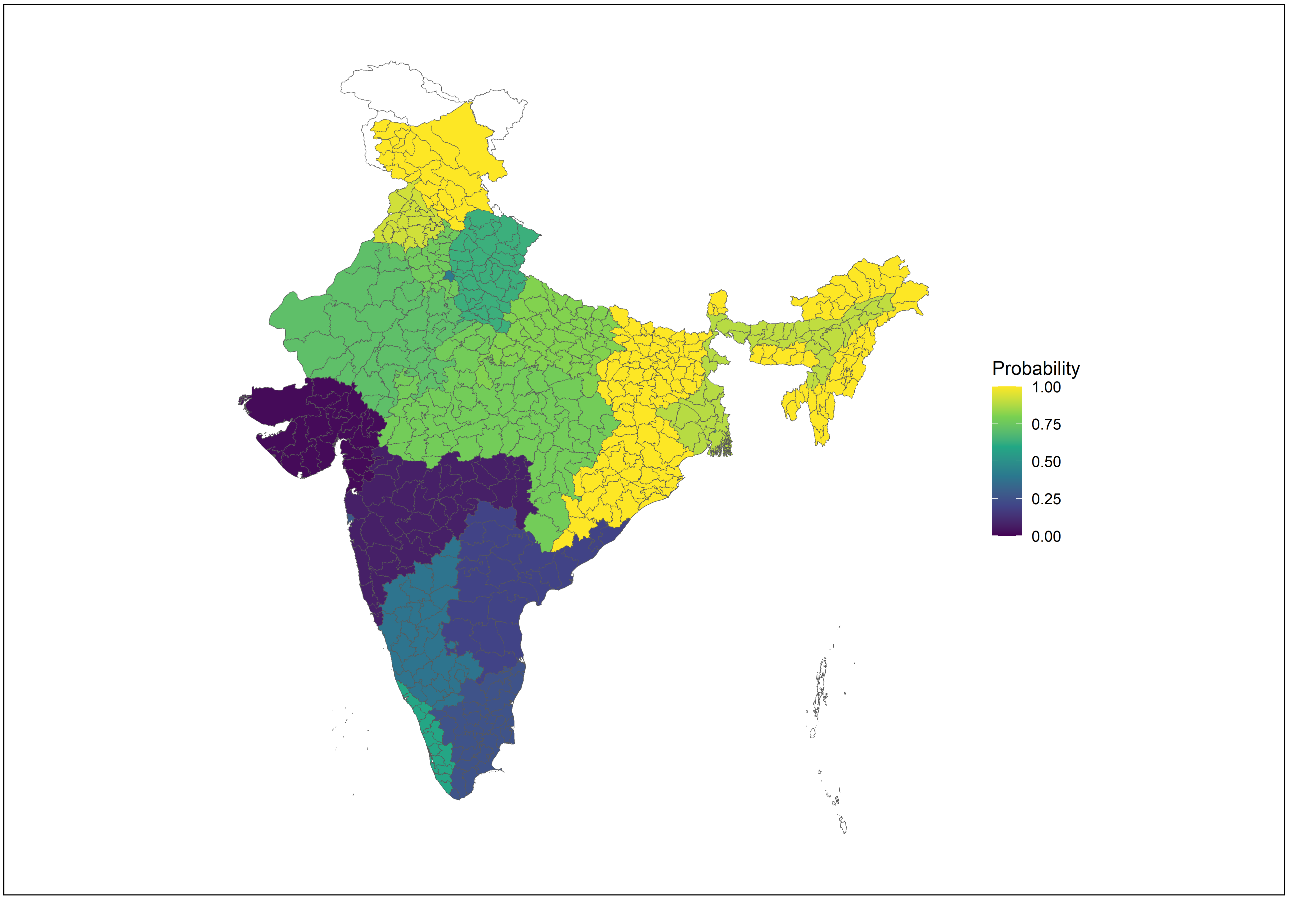


Figure 6: Plot of predicted probability of BSNL winning on the Indian map.

competition among the private service providers in the 2010 spectrum auctions. The price effect of BSNLs participation is negligible to negative in these circles. Due to its low predicted standalone value in these circles, the counterfactual shows that BSNLs participation in these circles fails to increase any price competition.

Circles with Probability of BSNL winning close to 1: In contrast, BSNL emerged as the winner with a probability close to one in circles such as the North East, Orissa, Bihar in the east and Punjab, Jammu & Kashmir, and Himachal Pradesh in the north. As shown in Figure 7, the counterfactual simulation highlights a clear geographical advantage for BSNL in these eastern and northern circles of India. This pattern is again consistent with BSNLs predicted ranking of circles reported in Table 4. However, due to BSNL's dominance over other operators in terms of predicted standalone values, BSNL's participation also fails to generate any meaningful price competition in these circles, as the incentives of the competing operators to outbid BSNL in these circles are low. In the 2010 auction, most of these circles were characterized by low prices and less intense bidding over rounds.

The earlier results suggest a pattern that circles with low stand-alone values tend to exhibit low BSNL win probabilities, while circles with high stand-alone values show a very high winning prob-

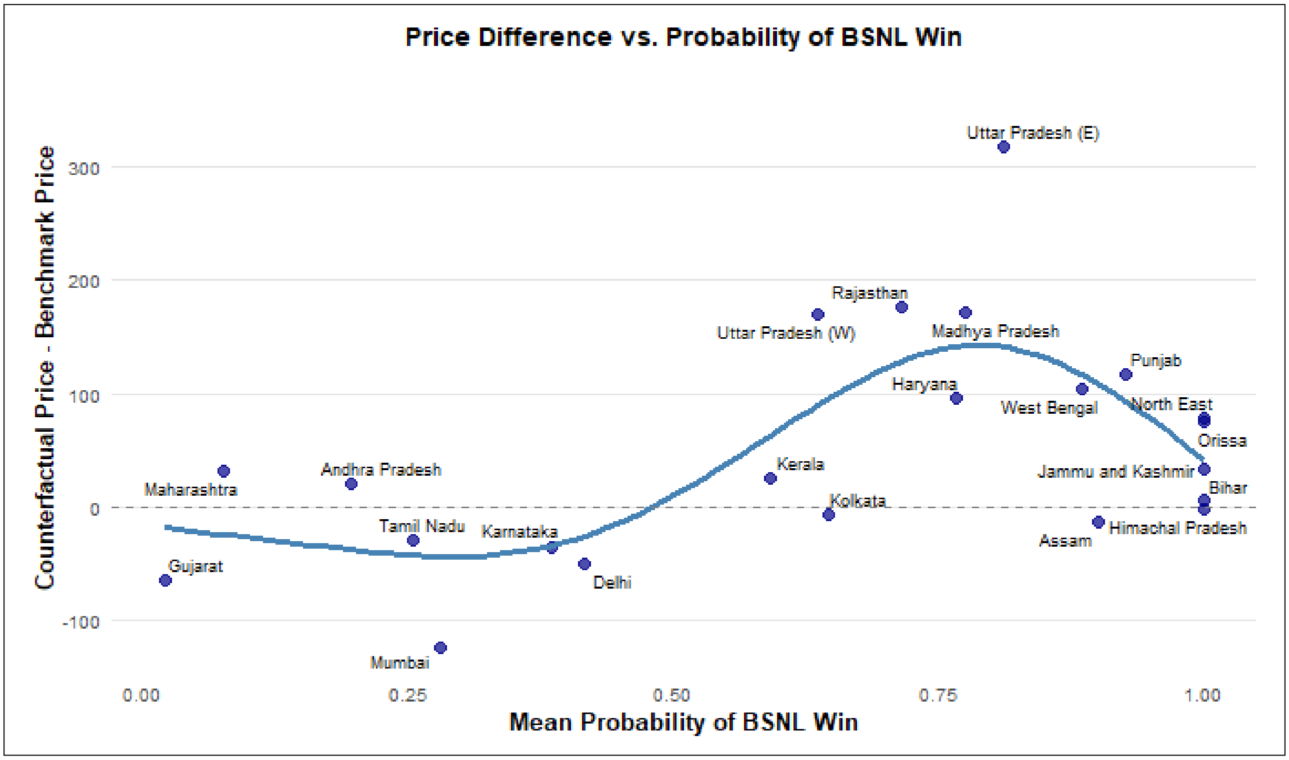


Figure 7: Plot of predicted probability of BSNL winning vs the increase in spectrum price for each circle in the counterfactual simulation. The X axis is the ratio of the number of times BSNL wins a circle to the total number of simulations and the Y axis is the difference between the average price difference of the circle between counterfactual and benchmark simulations. A positive value of the Y axis represents an average increase in price of the circle in the counterfactual.

ability for BSNL, but both show little or no impact on prices due to BSNLs participation. We then explore circles that exhibit an average increase in the winning price under the counterfactual and explain how license complementarities, and not only BSNL's standalone values, are responsible for driving the observed results. We observe that much of the competition driving prices upwards due to BSNLs participation occurs in circles that border its strongholds, where the probability of BSNL winning is close to one. Thus, these circles have a high marginal complementarity value for BSNL, but the ranking of BSNL only in terms of its predicted standalone value can range from very high to very low. We explore three distinct cases as follows.

High rank in terms of predicted value: Although BSNL ranks third in terms of its stand-alone valuation in Kerala (Table 4) and also enjoys one of the highest market shares in the circle, its performance in terms of win probability in the simulations is weaker compared to other circles with a similar private-value rank (Figure 7). While Kerala itself has a relatively high standalone value for BSNL, it is located in the southern region of India, surrounded by circles with comparatively low valuations. Hence, the marginal complementarity it adds to BSNL reduces due to Kerala having a high complementarity index with circles with a low probability of winning for BSNL. This reduces the incentive for BSNL to bid aggressively for Kerala, since the circle does not align well with its package-building strategy. In other words, Keralas standalone attractiveness is offset by its poor fit within a broader bundle of strategically valuable circles for BSNL. In contrast to this, we observe that Haryana, where BSNL ranks second in terms of its standalone valuation, has a higher probability that BSNL wins and also generates significant price competition. Unlike Kerala, this circle is geographically closer to other BSNL strongholds in northern India and has a higher expected marginal complementarity for BSNL.

Low rank in terms of predicted value: We observe that in Uttar Pradesh (W), BSNL ranks only fifth in terms of its standalone value, as shown in Table 4, but generates similar price competition as Haryana, as shown in Figure 7. Thus, we see that two circles with very different positions of BSNL in terms of its predicted standalone values perform comparably in terms of generating price competition. However, both these circles have a similar geographical location in terms of proximity to circles where the probability of BSNL winning is very close to one. This stands in contrast to Kerala, where, despite a high stand-alone value and large market share, the absence of valuable neighboring circles reduces complementarities and dampens BSNLs bidding incentives.

Middle rank in terms of predicted value: These circles also exhibit similar patterns as described above. We observe that much of the competition driving prices upwards due to BSNLs participation occurs in circles that border its strongholds but rank moderately in terms of their predicted stand-alone value. As shown in Figure 7, they include West Bengal, UP (E), and Madhya Pradesh bordering BSNL's eastern stronghold and Rajasthan bordering BSNL's northern stronghold. Because of their geographic proximity, winning these circles strengthens BSNLs ability to build a contiguous spectrum footprint, increasing the strategic value of the licenses well beyond their standalone valuations. In these cases, complementarities rather than intrinsic circle valuations amplify BSNLs incentive to bid aggressively, leading to sharper price effects than their stand-alone values alone would suggest.

Taken together, these patterns highlight how geographic complementarities shape bidding strategies amplifying competition and raising prices in some regions while dampening bidding intensity in others. The circles which generates higher winning prices in the counterfactual where BSNL participates in the auction have adds a high expected marginal complementarity value for BSNL due to their geographical location, but may have a rank ranging from very high to very low in terms of only the predicted circle level stand alone value. Importantly, our counterfactual simulations demonstrate that the model is able to capture these complementarities explicitly.

6.2 Subsidy Simulation

In the previous subsection, we have seen that our counterfactual results indicate a 7% increase in the national revenue when spectrums are allocated to the public providers through the SMRA auction, similar to that of the private providers. However, this increase in revenue comes at a cost in terms of access to public telecom operators for the beneficiaries, as, unlike a set aside, an all-India license is not guaranteed. We observe in our counterfactual that the expected percentage of the national population with access to BSNL's service reduces to 66.3%, which is detrimental to the universal service obligation.

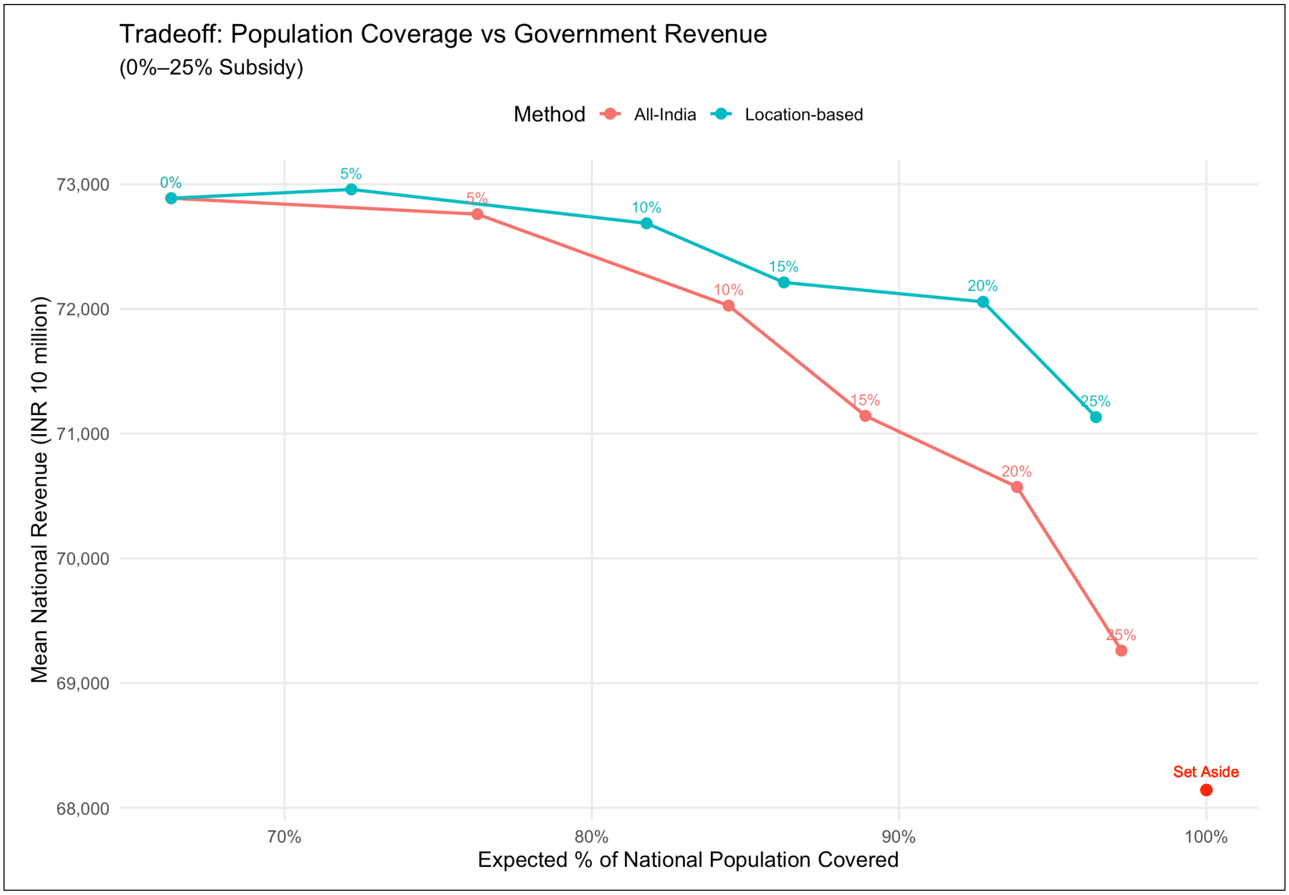


Figure 8: This figure plots the mean national auction revenue (in INR 10 million) against the expected share of the national population covered under two alternative subsidy mechanisms: an all-India uniform subsidy and a location-based subsidy. While both mechanisms expand coverage as the subsidy increases, the location-based design consistently yields higher revenues for comparable levels of population coverage.

We consider alternative subsidy-based mechanisms where, even though the spectrums are allocated to the public operator through the SMRA auction, it receives a price discount of a fixed percentage. We follow the minimum bidding set algorithm as described in the previous section, with the required price adjustment for the public operator BSNL. These subsidized counterfactuals explore the possibility of having a near-all-India BSNL service base with an increased national revenue compared to the set aside. We vary the discount rate from 5% to 25% and simulate the market outcomes under each level of subsidy. Using these different levels of subsidy, we also explore the tradeoff between revenue and access to the public operator, measured in terms of the expected share of the national population to have access to BSNL's service under these allocation mechanisms.

For each subsidy level, we consider two alternative mechanisms: (i) a **uniform subsidy**, under which BSNL receives a price discount in all available circles, and (ii) a **location-based subsidy**, under which BSNL receives a discount only in the southern and western circles and in the national capital region, while in all other circles it competes with private service providers for spectrum licenses in the SMRA auction at the competitive price. The rationale for the location-based subsidy is based on our results in our counterfactual analysis in the previous section, where the circles with a low probability of BSNL winning as shown in Figure 7.

A price subsidy can potentially help BSNL bid more competitively with the private bidders in the auction, improving its coverage as compared to the counterfactual outcomes without any subsidies. However, a targeted location-based subsidy can potentially achieve similar coverage as that of a uniform subsidy by only providing price discounts where BSNL performs poorly without price support. A uniform subsidy gives BSNL an advantage everywhere, including in circles where it may already be competitive, crowding out private bidders unnecessarily. A location-based design avoids unnecessary fiscal cost by focusing discounts only where BSNL needs them most, potentially achieving broader population coverage at a lower revenue sacrifice.

Figure 8 shows the tradeoff between the mean national revenue and coverage under the two alternative mechanisms for varying levels of subsidy. Our simulation results show that under both the subsidy mechanisms, BSNL's coverage can be increased as the rate of subsidy increases, with the expected share of the population having access to the public operator's services going above 95% under both mechanisms for a price discount of 25%. However, they do so at different costs to the national revenue. We find that for a discount rate of 20% above, a location-based subsidy achieves almost the same coverage goals at a higher mean national revenue. The mean national revenue under a uniform subsidy drops sharply after a subsidy rate of 10% compared to a location-based subsidy, where the tradeoff between mean national revenue and coverage is much more favorable.

The gap in the mean national revenues widens monotonically with the subsidy rate. The uniform subsidy delivers broader coverage relatively quickly but sacrifices revenue more steeply, since BSNL receives discounts even in circles where it is already competitive. By contrast, the location-based subsidy achieves a more favorable tradeoff: for comparable levels of population coverage, government revenue remains consistently higher. This reflects the efficiency of targeting subsidies only to regions where BSNL is relatively weak, ensuring that fiscal costs translate directly into expanded coverage rather than windfall gains in stronghold markets. A paired t-test for the mean difference shows that for all subsidy levels from 5% to 25%, the location-based mechanism yields significantly higher revenues than the uniform subsidy. The KolmogorovSmirnov (KS) test shows that at the 5% subsidy level, only the mean or median differs while the overall distributions remain similar, but from 10% onwards, both the central tendency and the distributional shape diverge sharply.

7 Conclusion

This paper provides the first structural analysis of spectrum auctions in India, focusing on the 2010 3G SMRA auction and comparing the existing *set-aside* mechanism for public operators with counterfactual *subsidy-based* allocation rules. This paper also contributes to the broader literature on market design in developing economies by analyzing a large-scale telecom spectrum auction in Indiaan emerging market characterized by rapid technological growth, mixed publicprivate participation, and substantial regional heterogeneity in infrastructure. To capture spatial interdependencies that are particularly salient in such settings, we introduce a novel *Train-based Complementarity*

Index, which quantifies the degree of connectivity between license areas using railway network data.

We demonstrate that allowing the public operator to participate in the auction, even without a price discount, can substantially increase national revenues by fostering competition. However, the benefits of such participation are highly heterogeneous across circles, driven by differences in stand-alone valuations and the spatial complementarities among licenses. Our counterfactual analysis reveals that location-based subsidies targeted at regions with strong complementarities among themselves and low win probabilities in the counterfactual are more effective in achieving comparable levels of coverage while preserving higher government revenue. These results emphasize that optimal protectionist policies must internalize both competitive dynamics and spatial complementarities among licenses when designing allocation mechanisms for mixed publicprivate markets.

While our analysis quantifies the trade-off between *coverage* and *revenue*, a natural next step is to move beyond revenue outcomes and coverage and evaluate the overall *welfare implications* of alternative allocation mechanisms. Future research could extend our framework by modeling consumer choices in the downstream telecom market to capture how spectrum allocation affects service quality, prices, and market shares. Combining the structural auction model with a demand estimation approach would allow us to measure how much of the governments implicit subsidy or revenue loss translates into consumer surplus and aggregate welfare. Such an integrated analysis of both the auction and post-auction markets would provide a more comprehensive understanding of the welfare efficiency of alternative spectrum allocation policies in developing mixed-market environments, such as India.

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Appendix

A Additional Tables and Figures

Table A1: Summary Statistics of Key Variables

Statistic	Max Price	Market Share	Total Population	Urban Ratio	Towers (2010)	Number of Rounds
Mean	765.0	0.0937	51,661,153	0.389	19,129	–
SD	962.0	0.0976	35,896,986	0.267	9,928	–
Min	30.6	0.0000	4,496,694	0.103	4,744	–
Q25	145.0	0.00000467	18,898,376	0.257	11,595	–
Median	322.0	0.0692	51,192,617	0.325	20,578	–
Q75	1212.0	0.170	72,620,904	0.416	25,699	–
Max	3350.0	0.352	128,477,824	1.000	38,392	183

Notes: This table presents descriptive statistics for key variables used in the analysis. 'Max Price' represents the maximum clock-round price per service area, while 'Market Share' is calculated at the bidder–service area level. 'Total Population', 'Urban Ratio', and 'Towers (2010)' are circle-level characteristics. 'Number of Rounds' refers to the total number of auction clock rounds conducted.

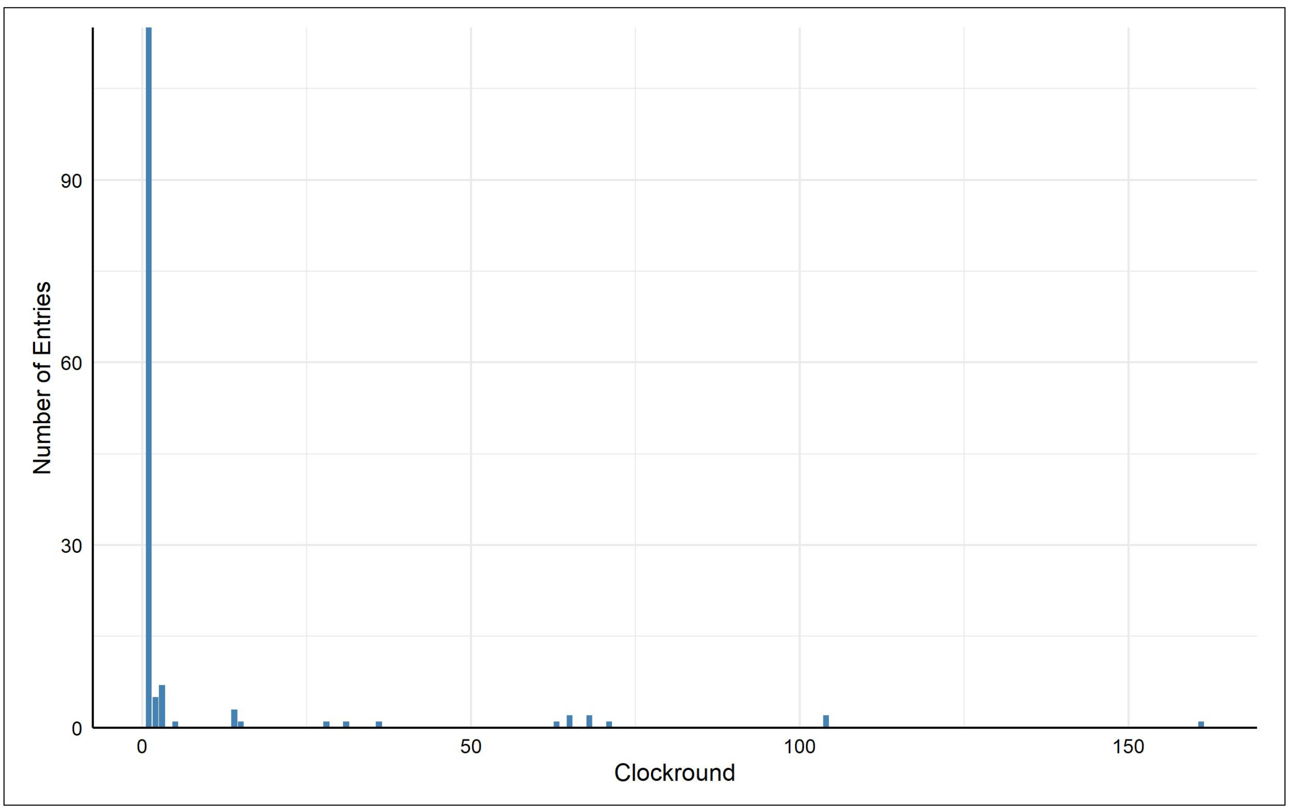

Figure A1: In the India 2010 spectrum auction for 3G there were nine unique bidders and 22 circles auctioned. Overall, this resulted in 144 unique bidder-license level entries. Out of which 127 occurred in the first three rounds. Further, there were only 12 distinct rounds where new entries took place, with at most three entries at round 14.

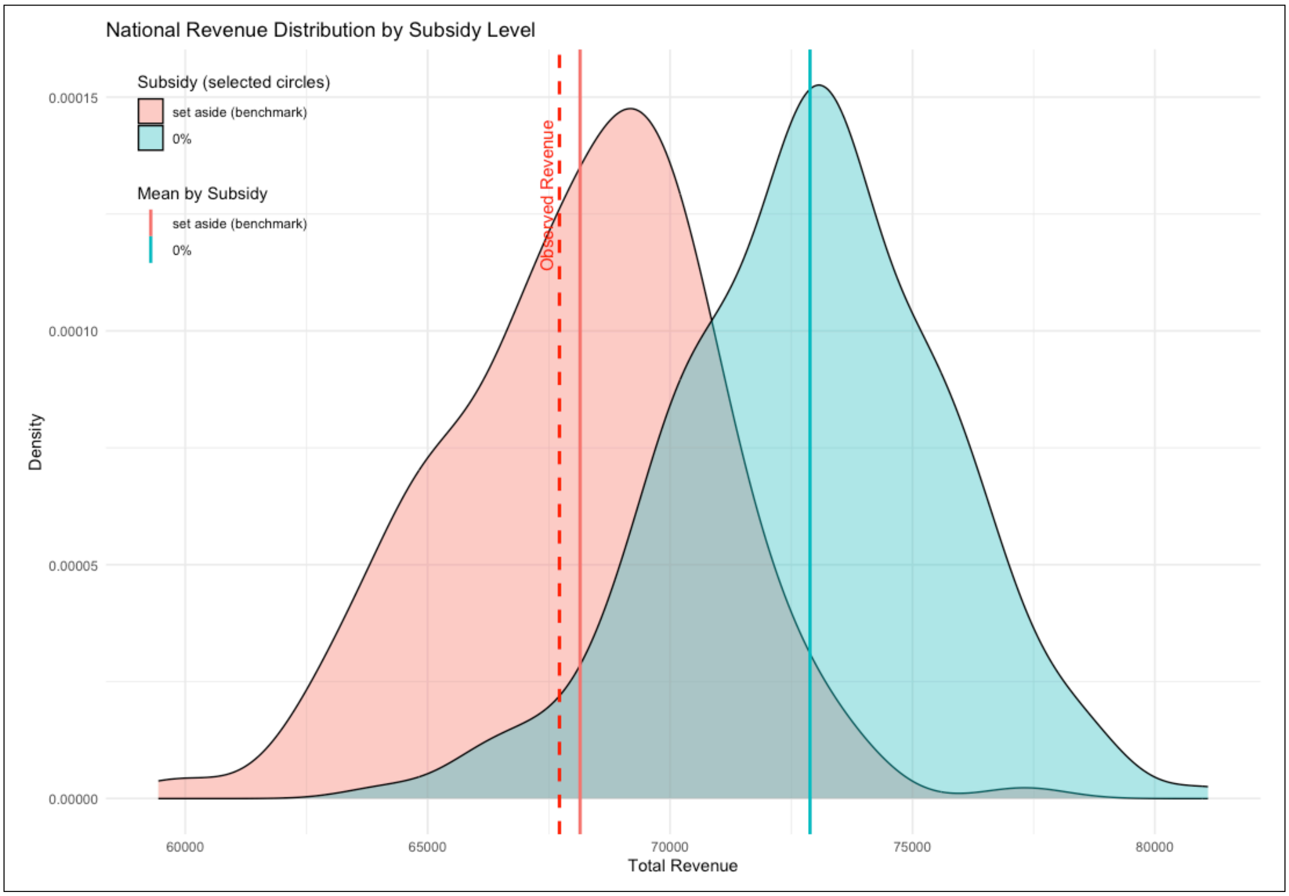

Figure A2: Distribution of all India revenue for the benchmark and the counterfactual simulations. The distribution of the benchmark simulation is shown in red, with the mean of the distribution marked with a vertical line of the same color. The red dashed line marks the observed all-India revenue, which is close to the mean of the benchmark simulation. The counterfactual distribution of the all-India revenue is shown in blue, where BSNL participates in the SMRA auction, and the distribution shifts to the right.

B Measurement of Good Voice Quality

The Telecom Regulatory Authority of India (TRAI) reports the metric *Good Voice Quality* as part of its Quality of Service (QoS) assessments. This indicator, expressed as a percentage, represents the proportion of voice calls that achieve or exceed a predefined standard of perceived call quality. The classification is based primarily on the *Mean Opinion Score* (MOS), a standard measure used globally to evaluate voice communication quality.

The Mean Opinion Score (MOS) is a numerical index ranging from 1 to 5, where 1 denotes *Bad* and 5 denotes *Excellent* quality. It reflects the average perceived clarity and naturalness of a voice call. MOS can be obtained through controlled listening tests or, more commonly, estimated using objective algorithms that emulate human auditory perception.[7]

To enable objective and scalable assessment, TRAI and service providers employ tools such as the *Perceptual Evaluation of Speech Quality* (PESQ). PESQ compares the original transmitted signal with the received signal to quantify degradation caused by compression, packet loss, or transmission delay, and converts this degradation into a MOS-equivalent score. TRAI defines a specific thresholdtypically a MOS value of 3.6 or higherto classify a call as having Good Voice Quality. Service providers collect and aggregate such MOS data through automated monitoring systems or user feedback to produce the final QoS statistics reported in TRAIs performance reports.

Percentage Calculation: The percentage of calls that achieve or surpass the predefined MOS threshold is calculated. For example, if 95 out of 100 calls have a MOS of 3.6 or higher, the "Good Voice Quality" metric would be 95%. By monitoring this metric, TRAI ensures that service providers maintain a high standard of voice communication quality, thereby enhancing user satisfaction.

[7] See ECS.UTDALLAS.EDU for technical documentation on MOS computation.