MATCHING IN THE CIVIL SERVICE: A MARKET DESIGN APPROACH TO PUBLIC ADMINISTRATION AND DEVELOPMENT

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Abstract. Using a matching theory perspective, I analyze the design and the impact of Indian Civil Service state assignment mechanisms used to allocate elite civil servants to different parts of the country. I find that a recent change in the matching mechanism in 2008 has systematically skewed assignments by assigning relatively poor quality bureaucrats to disadvantaged states: regions with external foreign conflict, states with internal political strife, and newly-formed states. This paper i) analyzes the causes of these imbalances, ii) assesses the impact of this mechanism change on state capacity, development outcomes, and bureaucratic performance, and iii) highlights trade-offs in implementing alternate mechanisms. Global balance in quality across state cadres is a unique constraint that arises when applying matching to political economy settings, as the mechanism designer is a paternalistic central planner. Thus, less is left to the market compared to most canonical matching applications. On the other hand, the use of matching in political economy is also novel, and careful understanding of how different matching mechanisms address underlying correlations in the data has far-reaching consequences for bureaucratic performance and development outcomes.

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1. Introduction

The Indian Administrative Service (IAS) is the topmost tier of the central government civil service. It administers a vast array of government operations at the state and federal levels from revenue collection and public welfare programs to public education and development schemes. Its importance is such that it is often referred to as the "Steel Frame of India."

Critical to the success of the IAS is the quality of its officers who are only 5,000 in number and are endowed with enormous power and responsibility. Officers are allocated using a matching mechanism. Each IAS officer is assigned at the beginning of their career to a state (or small group of states). This is a *lifelong* appointment and officers spend a vast majority of their careers in this location. Not surprisingly, this generates strong preferences among the applicants over location, correlated around the most desirable and against the least desirable locations.

The matching mechanism must sort between the applicants and their preferences. Moreover, the mechanism must also achieve the goals of the Indian government for the IAS, which themselves are considerable. The IAS, and the matching mechanism itself, has long been seen as an important tool to achieving national unity and well-balanced economics growth. Indeed, the Indian government has three stated objectives it aims to achieve with the mechanism. First, the government seeks a balance in quality, whereby talent is spread widely across the country. Second, affirmative action candidates must be distributed across states in proportions adhering to the national mandate. Third, while allowing for some home-preference for officers, excessive home bias must be avoided.

Given the importance of this matching procedure, it is important to understand the outcomes produced by the matching mechanism and analyze whether the system delivers on its intended purpose. The mechanism is a structured allocation problem with well-defined constraints, and thus amenable to analysis using the tools of matching theory. These tools, however, have thus far not been used to analyze a problem of this sort. The quality balance constraint and the application of matching to such personnel allocation problems at the heart of public administration and development, are new to the study of matching and market design.[1]

The objective of this paper is a broad analysis of the performance of the IAS matching mechanisms. We analyze the problem using all aspects of matching: we analyze the new constraints theoretically, we empirically analyze the match itself and the performance of assigned officers, and from an engineering design perspective we explore alternative matching mechanisms that may perform better. The main empirical strategy is to exploit a change in the assignment mechanisms implemented in 2008. Using structural break, difference-in-difference, and instrumental variable approaches, we use this change to show the impact of the mechanism and its resulting effect on development outcomes and state capacity. Specifically, we show that the new mechanism systematically assigns officers with 114.8 lower exam ranks to disadvantaged states and this leads to a divergence of \$206 million per year in tax revenues and 0.05 in Human Development Index across disadvantaged and advantaged states. If such imbalances are not addressed, vicious cycles can emerge: relatively higher

[1]Two recent working papers Sonmez and Yenmez (2019a, 2019b) also discuss IAS state allocation procedures, along with many other allocation procedures used by the Indian government, but focus entirely on the issue of overlapping horizontal and vertical affirmative action constraints arising from recently added affirmative action categories and court decisions in India.

quality civil servants avoid disadvantaged states, outcomes in these distressed areas further deteriorate, and the preference to avoid these regions is further reinforced.

The IAS *state cadre*[2] allocation process is transparent, algorithmic, and void of subjective internal evaluations or arbitrary political influence seen in subsequent transfer or promotion processes. Every year, the Union Public Service Commission (UPSC) holds a competitive Civil Services Examination[3] to select candidates for these prestigious civil service positions, and makes lifelong appointments assigning many new recruits to different state cadres: a *many-to-one matching* problem. The current allocation procedures only consider the preferences of candidates over state cadres, making this a *one-sided market.* In addition, the government seeks to impose *balance constraints across overlapping dimensions.* First, it seeks to limit too many candidates being allocated to their own home state of origin, what we refer to as the "*embeddedness dimension.*" While locally embedded officers are perhaps more willing and better able to serve the regions they are familiar with, being too familiar may also carry the risk of falling prey to local elite capture. Hence, for every officer who is assigned to his/her home cadre ("*insider*"), the UPSC tries to assign two officers ("*outsider*") whose home cadre is different from the assigned cadre. Second, the affirmative action policy in India mandates that seats be reserved for backwards classes: 15% for Scheduled Castes (SC), 7.5% for Scheduled Tribes (ST), and 27% for Other Backward Class (OBC). The UPSC sets relaxed exam score cutoffs for each of these groups and the mechanism tries to ensure each cadre's quota representation reflects the national mandate. We refer to this as the "*quota dimension.*" Lastly, the central government seeks balance across cadres over the exam rank of assigned candidates. Since exam rank is the only standardized proxy for quality the UPSC has at the time of initial assignment, the UPSC tries to achieve an equitable balance of quality of assigned officers across cadres. We refer to this as the "*quality dimension.*"

In this paper, we analyze the IAS state cadre assignment procedure from a matching theory perspective. First, we show that the change in the assignment mechanism in 2008 skews allocations by systematically assigning relatively poor quality, outsider candidates to *bad state cadres*: states which are newly formed, face external foreign conflict, and/or have internal political strife. Bad cadres get officers with 114.8 lower exam ranks on average as a result of the New Mechanism. We find that these imbalances can be attributed to the New Mechanism being more responsive to correlation in candidates' preferences over state cadres and to consistent patterns of disproportionate regional representation amongst exam toppers.[4] Under the New Mechanism, regional homophily also noticeably increased, with Northerners staying in Northern states, Southerners in South. This undermines the vision of proponents of the IAS, like India's first Home Minister and Deputy Prime Minister Vallabhbhai Patel, that the IAS promote national unity and integration.

[2]We use the official term, "state cadre," and "cadre" interchangeably to refer to a state or a group of states which forms an administrative unit as defined in the allocation process.

[3]See Appendix G for details on the Civil Services Examination. This paper focuses on these "direct recruits," who enter through the Civil Services Exam and take part in the cadre assignment mechanisms. Another way to enter the IAS is to be promoted from state civil services (see Appendix F); however, such promotees do not enter cadre allocation mechanism.

[4]We use the terms "exam toppers" and candidates interchangeably to refer to those who qualified by successfully clearing the Civil Service Exam cutoffs and are to be allotted cadres through the assignment mechanisms.

Second, we show that these systematic imbalances in the allocations also translate into imbalances in bureaucratic performance and developmental outcomes. By exploiting the exogenous change in mechanisms, we estimate that own tax revenue—which lies under the jurisdiction of early-career IAS officers— diverges by $206 million yearly across good and bad cadres, and bad cadres have a 0.05 lower HDI compared to good cadres under the New Mechanism starting in 2008. Furthermore, using the change in mechanism as an IV allows us to quantify the effect of bureaucratic quality (as proxied by exam rank) on tax revenue. We find that states assigned a set of officers with 1 lower average exam rank decreases own tax revenue by $13 million. This allows welfare analysis for counterfactual matching mechanism designs and alternative policies, such as varied affirmative action policies. We also find other imbalances caused by the change in mechanism, on characteristics that correlate with bureaucratic performance, as shown by results from the existing empirical literature. Bad state cadres tend to get candidates who are older and hence have less perceived bureaucratic effectiveness, candidates who are not amongst the highest scoring exam toppers and hence less likely to specialize and more susceptible to politicized transfers, and a higher percentage of outsider candidates who are less effective in public good provision.

Lastly, these imbalances motivate our study of how alternative mechanisms—two-sided matching, nudging preferences via incentives, preference restrictions, prioritized seats, and grouping cadres—can be designed to overcome such perverse, lopsided outcomes. Interestingly enough, we show that introducing two-sided matching can break the correlation in candidates' preferences that was feeding through the one-sided mechanisms, while also incorporating cadres' preferences over candidates' local language proficiency and specialization/education/work experience.

This highlights how matching theory can be applied to political economy.[5] In this novel application, the designer—the central government—is motivated by the desire of the IAS to live up to its All-India mandate and promise well-balanced development across all of India's state cadres. Thus, ensuring comparable bureaucratic quality across cadres is a distinct constraint with a particularly paternalistic flavor. In standard matching applications, 'more' is left to the market: the relative quality of students across schools and residents across hospitals, for example, are left to market forces and underlying preferences. There is no attempt to correct lopsided assortative outcomes such as the best students/residents being allocated to highly ranked, prestigious programs/hospitals. However, in our setting, the designer might want to constrain such systematic sorting.

Our results underscore a fundamental *Preference-versus-Performance Trade-off* a mechanism designer faces when correlated preferences and underlying correlations in covariates can lead to imbalanced allocations and assortative matchings. On the one hand, the designer wants to accommodate individuals' preferences to keep the members of the organization content, motivated, and prevent exists. However, this can come at a loss for the organization's performance and productivity as a whole.

After a brief introduction of the IAS (Section 2), we review the empirical literature on the IAS and the theoretical literature on matching with constraints (Section 3). Then we analyze the performance of the two most recent mechanisms: the Old Mechanism used from 1984 to 2007 and the New Mechanism used from 2008 to 2016 (Section 4). We analyze how and why these mechanisms cause imbalances in bureaucratic quality and national

[5]In a similar spirit, Thakur (2017) looks at the party-specific committee assignment mechanisms in the U.S. Senate from a matching theory perspective.

integration, and who benefits from the change in mechanism. In Section 5, we show that these quality imbalances translate to imbalances in state capacity, bureaucratic performance, and developmental outcomes. In Section 6, we suggest various market design possibilities to help overcome the imbalances by addressing the underlying correlations in the data (Section 6.1) and addressing the skew in origin of exam toppers (Section 6.2). Moreover, we analyze how various one-sided mechanisms address certain correlations in the preferences and in covariates (Section 6.3) and we introduce two-sided mechanisms with soft constraints (Section 6.4), to break the correlation from one-sided markets and incorporate cadre preferences over candidates' education, skills, and local language proficiency. We illustrate the fundamental Preference vs. Performance trade-off by comparing revenue-optimal and preference-optimal counterfactuals (Section 7). Finally, we highlight the broader applicability of the matching framework to other civil services and motivate other matching applications, outside of bureaucracies, which also call for incorporating quality balance constraints (Section 8).

2. The Indian Administrative Service

The IAS, along with other elite civil services like the Indian Foreign Service and Indian Police Service, evolved from the Indian Civil Service (ICS), which was used by the British to administer their Indian empire (1893-1946). Under British rule, many government functions like revenue collection, law and order, and general administration were streamlined under the management of very few ICS officers. Even today, the strength of the IAS is only around 5000 officers managing the administration of a country with a population of 1.3 billion. After Independence, it was this "Steel Frame" of Indian administration which proponents of the civil service system, most notably India's Deputy Prime Minister Sardar Patel, sought to maintain. Some opposed its continuation, viewing the IAS as a remnant of the imperial administration acting against the interests of sovereign India. However, Patel and others maintained that the All-India services would preserve unity and integration over the diverse country which included a conglomeration of princely states at that time.

IAS officers are central government civil servants who are given lifelong assignments to a certain state cadre. Although IAS officers can be temporarily deputed to a different cadre or promoted to the Centre, a vast majority of an IAS officer's career is spent in his assigned state. Even the early-career positions given to younger IAS officers such as District Magistrates or District Collectors carry a lot of power and responsibility: managing revenue collection, supervising law and order, serving as custodian to government land, and implementing government policies. Over their careers, IAS officers are transferred across districts within their cadre and promoted to higher positions of Joint Secretary of Ministries or Cabinet Secretary based on seniority, internal performance evaluation, and political influence arising from ministerial approval. Thus, more senior posts involve policy implementation and advising or even drafting legislation alongside elected officials. Some IAS officers choose to pursue higher education. The skills and expertise acquired by experience, training, and further education can help in getting better positions, promotions up the hierarchy, or empanelment[6] to the Centre. Hence, working with state civil servants, state and federal politicians, IAS officers serve in the highest-tier administrative positions ranging from overseeing agricultural policy, land revenue and district administration, to working with NGOs to administer rural development projects and setting higher education policy.

[6]Empanelment refers to the selection process of civil servants to be appointed to top bureaucratic positions of joint secretary and higher in the Central Government of India.

3. Literature Review

Instead of providing an overarching review of the theoretical and empirical literature on bureaucracies,[7] we contextualize this paper amongst two strands of literature: first, the empirical literature on the IAS and second, the theoretical literature on matching with constraints.

Iyer and Mani (2012) and Nath (2015) focus on the interaction between career bureaucrats and their politician counterparts. Iyer and Mani (2012) emphasize the vast discretion over transfers and promotions which lies in the hands of the state ministers. They find that the probability of an IAS officer being transferred increases by around 10% when a new minister is elected. Furthermore, top-20 exam rank officers are transferred less frequently compared to the rest of the IAS officers. Thus, Iyer and Mani posit that IAS career success can be brought about via two substitutable avenues: enhancing one's skills or exhibiting political loyalty. Nath (2015) measures bureaucratic performance by the time it takes for IAS officers at the district collector level to sanction projects proposed by Members of Parliament and funded with discretionary funds. When incumbents are barred from being re-elected (when the seat comes under an affirmative action reservation quota), the time to sanction a project increases by 13%. Moreover, when the seat is a party stronghold and the incumbent politician is likely to be re-elected, projects are approved 11% faster. Finally, when the district collectors are eligible for promotion, the quality of implementation improves. Together, these papers show how politicians can impose control over IAS officers via their career trajectory; however, this only applies later on in their careers. Our paper deals with the initial cadre assignments at time of entry into the IAS, which is governed by the well-specified matching algorithm. Hence, we do not have to worry about political influence in this process.

The other strand of empirical literature on IAS studies the different characteristics that predict effective bureaucratic performance and improved developmental outcomes. Ferguson and Hasan (2013) find that investment in specialization of skills, through education and training, benefits IAS officers throughout their careers. Early on in their career, investment in specialization acts as a signal of general ability and increases the chances of getting promoted to the Centre. However, their posting in New Delhi does not necessarily match their skills or area of expertise. On the other hand, later in their careers, when up for Empanelment, IAS officers who specialize are rewarded for their skill acquisition as their posting reflects their area of expertise. Bertrand et al. (2015) form their own measure of perceived bureaucratic effectiveness by surveying local "societal stakeholders" such as NGOs, businesses, politicians, and other civil servants. They find that higher exam score, better training performance, and younger age predicts higher perceived bureaucratic effectiveness. Furthermore, perceived bureaucratic effectiveness score is associated with faster growth, increased revenues, and more development expenditures. Hjort et al. (2015) find that education, local language proficiency, and direct recruitment predict higher value-added officers. Moreover, high value-added bureaucrats predict better project outcomes, higher

[7]Theoretical models of delegation and political oversight include McCubbins, Noll, Weingast (1987, 1989), Moe (1989, 1995, 2005, 2012), Epstein and O'Halloran (1999), Bendor and Meirowitz (2004), Huber and McCarty (2004), Huber and Shipan (2011), and Gailmard and Patty (2012), and empirical work testing theories of delegation includes Gulzar and Pasquale (2017). See reviews of survey analysis related to bureaucracies and civil services (Rogger (2017)), field experiments in personnel economics (Finan et al. (2017)), and work on state capacity and its impact on development (Bandiera et al. (2014)).

nighttime luminosity, and increased likelihood of future empanelment. Bhavnani and Lee (2015) find that insiders increase public goods provision (as measured by percentage of villages in district with schools), but only when districts have a high level of accountability, as proxied by high literacy and strong newspaper circulation. However, a recent working paper Xu et al. (2018) suggests that insiders perform worse than outsiders on perceived bureaucratic effectiveness. They use surveys of insiders and outsiders from 14 major states and instrument for the likelihood of being assigned an insider position by the size of the exam topper cohort in the same quota category originating from that state cadre.

We use many of these empirical findings in Section 5.3 to assess the impact of the assignment mechanisms on developmental outcomes and bureaucratic performance.

The literature on constraints in matching theory has largely revolved around the canonical applications in matching: regional caps and Rural Hospital problem in residency matching, and affirmative action in school choice.

The residency matching market, such as the National Resident Matching Programs in the US (NRMP) and Japan (JRMP), tends to be an imbalanced market with more hospital vacancies than residents. Furthermore, candidates tend to prefer urban placements over rural placements. Hence, the early matching mechanisms used in these settings (candidate-proposing Deferred Acceptance) suffered from urban areas being over-served while inner-city and rural areas were under-served. Roth (1984, 1986) establishes the seminal Rural Hospital Theorem, proving that when candidates have strict preferences, any hospital that fails to fill its vacancies in some stable matching, will not only fill the same number of candidates, but will also be filled by the same set of candidates, in any stable matching. This general result meant that the attractive notion of stability in two-sided markets has to be compromised in order to alleviate such maldistribution of candidates. Kamada and Kojima (2014, 2017) theoretically analyze how to incorporate distributional constraints in the form of regional caps in two-sided matching. Their Flexible Deferred Acceptance Mechanism is constrained pareto optimal and "strongly stable." The notion of strong stability ignores unjustified envy for blocking pairs which are infeasible due to the constraints. In our paper, since the market is balanced[8] and preferences cannot be truncated (i.e., there are no unacceptable matches from the perspective of either the candidate or the cadre), the concerns of unfilled vacancies, rural hospital theorem, and regional caps do not apply to the IAS matching problem. However, the government's attempt at designing mechanisms to undermine regionalism and promote movement of candidates across the country is derived from similar underlying motivations (see Section 6.1.2).

In school choice and many other applications, affirmative action and legally mandated quotas/reservations for gender, race, or socio-economically under-privileged candidates are quite common constraints which must be accommodated.[9] This literature highlights two important considerations for incorporating such constraints in two-sided matching. First, it is imperative to weaken the notion of stability to justified envy: blocking pairs which are not feasible due to the priorities and quota restrictions are ignored. Second, these papers

[8]The UPSC chooses exactly the same number of IAS candidates from the Civil Service Examination as there are vacancies.

[9]See Abdulkadiroglu and Sonmez (2003), Abdulkadiroglu (2005), Ergin and Sonmez (2006), Dur et al. (2016), Abdulkadiroglu et al. (2009), Kojima (2012), Echenique and Yenmez (2015), Westkamp (2013), Hafalir et al. (2013), and Ehlers et al. (2014) for affirmative action and quotas in school/college choice. For affirmative action and quota constraints in other applications see Sonmez (2013), Sonmez and Switzer (2013), and Delacretaz et al. (2016).

collectively highlight the differences in using hard constraints (i.e., seats explicitly reserved for quota candidates) versus soft bounds (i.e., seats prioritized—but not reserved—for quota candidates).

Our paper differs from the school choice with constraints literature because when we introduce two-sided matching, it is with the intention of i) incorporating cadres' preferences over candidates on the basis of local language proficiency, education and skills, and ii) breaking the correlation in preferences with one-sided matching (see Section 6.4). However, we do use soft constraints across overlapping types (Ehlers et al. (2014) and Kurata et al. (2017)) to i) incorporate IAS constraints over exam rank, embeddedness, and quota (see Section 6.4.1) and ii) promote regional mobility (see Section 6.1.2). Abdulkadiroglu (2005) examines college choice with affirmative actions where colleges have preferences over subsets of students, and describes two properties college preferences must satisfy for Deferred Acceptance to maintain its desirable properties. This would be interesting to incorporate when we introduce two-sided matching; however, to keep the assumptions behind the simulations at a minimum, in this paper we assume cadres have preferences over individual candidates, and not groups of candidates.

Two recent papers by Sonmez and Yenmez (2019a and 2019b) focus on simultaneously dealing with both vertical (such as General, OBC, SC, and ST quotas and the newly introduced economically weaker section in 2019) and non-nested horizontal affirmative action categories (such as gender and disability). Such settings arise in Indian public sector jobs, civil service, and education sector and result in complications due to individuals potentially qualifying for multiple affirmative action categories and qualifying from non-reserved exam score cutoffs despite being from an affirmative action category. They propose implementing Deferred Acceptance with a novel choice rule so as to maintain the nice properties of eliminating justified envy across exam ranks, both within affirmative action category and across these categories. In this paper, we do not consider these horizontal affirmative action categories. There are no gender quotas in the All-India Services and candidates with disabilities are extremely few in number.

4. Evaluating the 1984 & 2008 Cadre Allocation Mechanisms

The UPSC, which is the central government agency in charge of recruitment, has experimented with many matching mechanisms for the assignment of IAS recruits to states cadres. Two recent systems are the 1984-2007 system (Section 4.1) and the 2008-2016 system (Section 4.2). We will show that the 2008 New Mechanism causes imbalances in quality, systematically hurts certain certain states because it takes preferences of candidates 'too seriously,' and leads to greater homophily (Section 4.3). Furthermore, we identify which groups benefit/lose from the change in mechanism (Section 4.4).

Readers interested in understanding mechanism in full detail should read Sections 4.1 and 4.2. Those less interested in exact details of the mechanisms can skip to either the key features of each of the mechanisms (Table 1) and/or the flowchart summary of the two mechanisms (Figure 1).

4.1. **The 1984 "Old Mechanism."**

The Old Mechanism was in place from 1984 to 2007.[10]

[10]The official assignment process rules are clearly delineated by the UPSC and are available online at http://persmin.gov.in/AIS1/Docs/OldCadreAllocProcedure.pdf. In this paper, we abstract away from special rules for candidates from quota who qualified under the general category cutoff for exams (Section 4)

Table 1. Key features of the Old and New Mechanisms.

Old Mechanism (1984-2007)	**New Mechanism** (2008-2016)
1. Priority given to insiders in order of exam rank.	**1.** Priority given to insiders in order of exam rank.
2. *Only preference of civil servants is whether or not want insider position*	**2.** *Full preference rank order of civil servants over all cadres.*
3. Outsiders allocated by a complicated formula, but unpredictable, as-if-random from officers perspective.	**3.** Outsiders allocated by a serial dictatorship in order of exam rank.
4. Prioritizing certain states over others across years and by prioritizing states which failed to get many high-ranking Insiders, for being assigned high-ranking Outsiders.	

(1) The 24 cadres are split into 4 alphabetically ordered groups[11]:
- Group I: Andra Pradesh, Assam-Meghalaya, Bihar, Chhattisgarh, Gujarat
- Group II: Haryana, Himachal Pradesh, Jammu & Kashmir, Jharkhand, Karnataka, Kerala, Madhya Pradesh
- Group III: Maharashtra, Manipur-Tripura, Nagaland, Orissa, Punjab, Rajasthan, Sikkim
- Group IV: Tamil Nadu, AGMUT, Uttarakhand, Uttar Pradesh, West Bengal

(2) Each year, the order of the 4 groups is rotated by moving the first group to be the last. This forms a permutation of the 24 states. The algorithm goes through this ordered list again and again in a cyclical fashion as we explain below, hence we call this a "1:24 cycle." For example, the 2007 rotation was 1) Group IV, 2) Group I, 3) Group II, and 4) Group III. Hence, Bihar which is the 3rd state in Group I becomes the 8th state in the 1:24 cycle in this rotation.

(3) Each cadre creates a list of vacancies across 6 groups: insider and outsider vacancies separated by the 3 quota categories (General, OBC, SC/ST).

(4) Candidates are arranged by exam score and each candidate is asked whether or not he would like to be considered for an insider position.[12]

(5) First, in order of exam rank, all those who answered "Yes" to being an insider, are allotted to their state if there is a corresponding vacancy in their quota category.

vii)). See recent work by Sonmez and Yenmez (2019a and 2019b) on the challenges of incorporating these "horizontal" affirmative action considerations and the surrounding legal context.

[11]This mechanism is used for all simulations of the Old Mechanism in this paper. To stick with this original ordering, we avoid running counterfactual Old Mechanisms for years 2014 onwards because Telangana was formed and Manipur-Tripura were split. We also avoid running this Mechanism for years before 2001, because in 2000 the new states Jharkhand, Chhattisgarh, and Uttarakhand were formed.

[12]In our simulations we assume that everyone wants to be an insider. This is close to reality in that almost everyone answered "Yes" to this question as this mechanism otherwise gave a seemingly random allocation from the perspective of the candidate.

(6) Next, if there are insider vacancies with no matching candidates who are willing to be insiders, check for swaps (in order of exam rank):
   - If there is no General insider candidate to fill a General insider vacancy, first check if there is an SC/ST insider candidate, SC/ST insider vacancy, and SC/ST outsider vacancy which can be exchanged: SC/ST insider vacancy is deleted, an SC/ST outsider vacancy switches to General outsider vacancy, and the candidate is allotted to the cadre. If no SC/ST insider candidate or no SC/ST outsider vacancy, attempt for similar swap with OBC category. Similarly, if no OBC insider vacancy is filled, check for swaps first with SC/ST category and then with General category. And then, if no SC/ST insider vacancy is filled, check for swaps first with OBC category and then with General category.[13]

(7) If an insider vacancy remains even after swaps, convert it to an outsider vacancy.
(8) Insiders in each state are allocated into subsequent 1:24 cycles. Then in the remaining subsequent cycles, introduce any existing outsider vacancies by each state. For example, if Maharashtra gets 4 insiders, they are allotted to cycles 1, 2, 3, and 4 respectively, and Maharashtra's remaining vacancies for outsiders will be allotted to cycles 5, 6,...
(9) Arrange all remaining candidates in order of exam rank and go through the 1:24 cycles to fill remaining outsider vacancies by order of exam rank. However, rotate groups every cycle when allotting insiders (i.e., group 1 of this year's rotation is first in 1st cycle, group 2 is first in 2nd cycle, etc).

4.2. **The 2008 "New Mechanism."**

The New Mechanism has been in place from 2008-2016.[14] Now, the groups and 1:24 cycles from the Old Mechanism are not used.

(1) Each candidate is asked to report their strict preferences over cadres.[15] Those who rank their home state as their top choice are considered for insider positions.
(2) Each cadre creates a list of vacancies across 8 groups: insider and outsider vacancies separated by the 4 quota categories (General, OBC, SC, and ST).[16]
(3) First, go through candidates by exam rank and allot those who want to be insiders to cadres if a matching vacancy in their category exists.

[13]During the swaps, disabled insider candidates are given highest priority, however, we omit this from the simulations.

[14]The official assignment process rules are clearly delineated by the UPSC and are available online at http://persmin.gov.in/AIS1/Docs/NewCadreAllocPolicy.pdf. In this paper, we abstract away from special rules for physically disabled candidates (Section 5c) and candidates from quota who qualified under the general category cutoff for exams (Section 9). See recent work by Sonmez and Yenmez (2019a and 2019b) on the challenges of incorporating these "horizontal" affirmative action considerations and the surrounding legal context.

[15]Caveat for truncated preferences: "If a candidate does not give any preference for any of the cadres, presume he has no preference. Accordingly, if he is not allotted to any one of the cadres for which he has indicated preference, he shall be allotted along with other such candidates in the order of rank to any of the remaining cadres, arranged in alphabetical order, in which there are vacancies in his category after allocation of all the candidates who can be allotted to cadres in accordance with their preference." Hence, there are no unacceptable cadres by the rules.

[16]Because the Old Mechanism vacancies reports SC and ST vacancies combined as one group, to allow for the coarsest vacancy reporting so that we can run comparable counterfactual New Mechanisms, in the simulations, we always combine SC and ST vacancies for years 2008 onwards.

(4) Next, if insiders do not have matching vacancy in their quota category, check for swaps:
   - When no candidate is available against an insider SC Vacancy, check for swaps by exam rank first with ST insider candidate, then OBC insider, and then General insider by shifting the SC vacancy to the cadre which the incoming officer would have otherwise been allocated to as an outsider[17] (if this does not work, swap with the next cadre in alphabetical order in which outsider vacancy is available). Similarly, insider ST Vacancy checked for swaps by exam rank first with SC, OBC, and then General insiders. Insider OBC vacancy checked for swaps by exam rank first with ST, SC, and then General insiders. Insider General vacancy checked for swaps by exam rank first with SC, ST, and then OBC insiders.

(5) Convert all remaining vacancies to outsider vacancies.

(6) In order of exam rank, run through each candidate's preference order and allocate if vacancy exists.[18] [19]

[17]In our simulations, we run the counterfactual with a random preference we generate by assumption when we do not have the actual preference orders of the candidates.

[18]Caveat if no vacancies other than home state remain, swap candidate with first candidate above him (by exam rank) who has been allocated as an outsider. We omit this in the simulations because we always assume a candidates' first choice is to be an insider.

[19]It is not specified what assumption is made if the vacancy quota does not match. For example, it is unclear what happens to say an excess SC candidate when there are no SC vacancies left as well as the case when there are SC vacancies left, but no SC candidates. Such details are omitted in the official procedure write-up. Hence, in our simulations, for the outsider stage, we combine vacancies across all quota categories for each cadre and allocate accordingly.

Figure 1. Flowchart of the Old Mechanism (1984-2007) and New Mechanism (2008-2016)

1st STAGE: INSIDERS & SWAPS

COMMON TO BOTH MECHANISMS

(1) PRELIMINARIES

a) Form an ordered list of candidates ranked in order of exam scores

b) Create a roster of vacancies for each cadre, delineating number of vacancies in each embeddedness x quota category

(2) INSIDERS

In order of exam rank, assign all those who want to be insider (answered "Yes" to Insider Question in Old Mechanism OR ranked home state as their top preference in New Mechanism) if a vacancy exists in their quota category

(3) SWAPS

For any unfilled insider vacancies, check for swaps in order of exam rank:

i) If there is no General insider candidate to fill a General insider vacancy, first check if there is an SC/ST insider candidate, SC/ST insider vacancy, and SC/ST outsider vacancy which can be exchanged: SC/ST insider vacancy is deleted, SC/ST outsider vacancy switches to General outsider vacancy, and candidate is allotted to the cadre. If no SC/ST insider candidate or no SC/ST outsider vacancy, attempt similar swap with OBC category.

ii) Similarly, consider swaps for unfilled OBC insider vacancies

iii) Similarly, consider swaps for unfilled SC/ST insider vacancies

2nd STAGE: OUTSIDERS

OLD MECHANISM

a) Ordering of the 4 Groups is rotated to fix a permutation of the 24 cadres (we call "1:24 cycle").

b) Allocate all those who were allocated as insiders (both through merit and through swaps) into subsequent cycles for each cadre.
(i.e., if Kerala has 2 insiders, the first one is allotted to Kerala in 1st cycle and 2nd is allocated to Kerala in 2nd cycle)

c) Change group rotations across cycles
(i.e., if the 1:24 cycle has Group 2 at top, 1st cycle has Group order 2-3-4-1, 2nd cycle has Group order 1-2-3-4, 3rd has 4-1-2-3, etc. In total, there will be K cycles, where K is the maximum number of vacancies any cadre has. Note that only cadres with at least n vacancies will have a vacancy in the nth cycle)

d) Allocate all vacancies which remain unfilled in order of this permutation of cadres in c), by allotting candidates who remain in order of exam rank

(Note: not allowed to be allocated to home cadre in this stage, so swap with above if such an occurrence occurs in the permutations)

NEW MECHANISM

Serial Dictatorship for all remaining candidates who haven't been assigned as insiders:
I.e., in order of exam rank, match candidates to vacancies based on complete preference rank order of candidates over cadres.

(Note: not allowed to be allocated to home cadre in this serial dictatorship stage)

4.3. **Distributional Asymmetries and Their Causes.**

4.3.1. ***Systematic Imbalances due to the Mechanisms.***

As a result of the change in cadre assignment mechanisms, systemic imbalances across state cadres become apparent. The variance of within-cadre average exam rank across all cadres jumps by about 5-fold under the New Mechanism compared to the Old Mechanism (Figure 4). Hence there is a striking increase in the inequality across cadres as to the bureaucratic quality of incoming IAS officers.

To better understand where this distributional asymmetry in bureaucratic quality arises, we compare average bureaucratic quality for each state cadre—i.e., the cadre's average exam rank—from the actual assignment with that from many draws of random assignments. We want to compare what fraction of random allocations within quota[20] give better average exam ranks for each state compared to their actual assignments. Figure 5 highlights for a subset of the cadres, that while cadres tended to switch across years from under-performing to over-performing random assignments under the Old Mechanism, under the New Mechanism, you have certain state cadres systematically under-performing random allocations. Figure 6 shows the year-by-year comparison for all 24 cadres, comparing the percentage of time a cadre's actual average exam rank is above the average exam rank produced by random within quota mechanism simulations. Hence, the orange line at 50% implies the state is assigned an average quality similar to random. A point above 50% means the state has under-performed relative to random assignments while below 50% implies the state over-performs. We see from years 2005-2007 during the Old Mechanism, that the rotation of groups across years caused an equalizing effect whereby cadres switched from under-performing to over-performing across years. However, starting from 2008 onward, with the New Mechanism, a certain group of states consistently tend to under-perform relative to random assignment.[21]

Overall, we identify certain states which are systematically and disproportionately harmed by the New Mechanism's allocations, and from now on, refer to them as "*bad cadres*:"

(1) Nagaland
(2) Assam-Meghalaya
(3) Manipur
(4) Tripura
(5) Sikkim
(6) Jammu and Kashmir
(7) West Bengal
(8) Chhattisgarh

As shown in Figure 2, these states are concentrated in the north and northeast, and have very unique political climates. First, Nagaland, Assam-Meghalaya, Manipur, Tripura, and Sikkim all are part of the Northeastern Bloc, where there is external foreign conflict, disputed territory with China, many indigenous tribes leading to internal political strife and heavy military presence. Second, Jammu and Kashmir borders Pakistan and historically has had

[20]The random within quota mechanism first takes quota seats and randomly fills them with quota candidates. Then pools the leftover quota candidates with non-quota candidates and randomly assigns them to remaining vacancies.

[21]In Figure 7, we note that if we compare the percent of times that the actual mechanism leads to a lower mean of average exam rank across cadres (Left) and lower variance of average exam rank across cadres (Right), the Old Mechanism vastly outperforms the fully random and random with quota mechanisms where as the New Mechanism vastly under-performs relative to the random mechanisms.

wars and struggles with Pakistan over disputed territory along with a long history of war, military presence, and violence. Third, West Bengal is an eastern state with many Naxalite communist factions and internal political strife and violence. Finally, Chhattisgarh is a relatively new state carved out from Madhya Pradesh in 2000. Hence, this list of bad cadres is characterized by a) external foreign conflict, b) internal political strife, and c) new states. As an example illustrating the political and regional instability in these areas, Figure 8 shows the 0.57 correlation between the cadre's average preference rank by candidates and the number of terrorist attacks (1970-2015).

Figure 2. The cadres adversely affected by the New Mechanism by being systematically assigned relatively lower quality candidates and more outsider candidates: Nagaland, Assam-Meghalaya, Manipur, Tripura, Sikkim, Jammu & Kashmir, West Bengal, and Chhattisgarh.

Figure 9 shows the average exam rank across for the bad cadres and good cadres (defined as the complement of the bad cadres). The parallel trend, more yet, the fully comparable average exam rank across bad and good cadres, then undergoes a divergence under the New Mechanism. Using a difference-in-difference strategy, we estimate that as a result of the change in mechanism bad cadres receive candidates who are 114.8 exam ranks lower on average, or 0.784 standard deviations lower than the national average (Table 2).

4.3.2. ***Causes of such Imbalances.***
The imbalances resulting from the New Mechanism are primarily driven by (1) a concentration by region as to from which states the exam toppers originate and (2) correlated preferences candidates have over over which cadres are good versus bad.

We see from Figure 10, that across both mechanisms and within each quota category, insiders have lower exam rank (i.e., better quality) than outsiders. However, bad cadres tend to produce few exam toppers relative to their total vacancies (Figure 11). Since the sought-after balance of insiders to outsiders is set at 1:2, states with a ratio less than 0.33 will definitely not be able to fill insider vacancies. Since both Old and New Mechanisms favor insiders by giving them first priority, this puts many of the bad cadres at a comparative loss. Bad cadres not only tend to place fewer exam toppers, but also lower quality exam toppers (Figure 12).

Table 3 summarizes how the two mechanisms differentially address the asymmetry across states' abilities to produce exam toppers. The insider priority common to both the Old and New Mechanisms benefits cadres which produce many exam toppers with good exam ranks (Columns (1) and (2)). However, while the Old Mechanism's group rotations causing different priorities in the 1:24 cycles compensates states who failed to get high ranking insiders with priority over outsiders of better exam rank (Columns (3) and (4)). Whereas the New Mechanism does not have any such correction feature.

Moreover, under the New Mechanism, IAS candidates exhibit highly correlated preferences with a reasonable consensus over which cadres are good versus bad. Benbabaali (2008)'s survey of IAS officer's top 5 (Figure 13 Left) and bottom 5 (Figure 13 Right) cadre preferences corroborates this.[22] The states ranked amongst the top 5 map well to those we call the good cadres, while the states ranked amongst the bottom 5 align with the bad cadres. The northeastern bloc (Assam-Meghalaya, Nagaland, Sikkim, Manipur, and Tripura) face foreign conflicts over disputed territory with China and internal conflicts involving indigenous tribes.[23] Jammu and Kashmir has long been disputed territory with Pakistan and China, while West Bengal has internal struggles with Naxalite factions.

We have cadre preference data for the Indian Police Services batch 2008 and Indian Forest Services batches 2015 and 2016 under the New Mechanism, where we also observe high correlation coefficients of 0.57, 0.48, and 0.52 respectively.[24]

4.3.3. ***Discrete Choice Analysis of Cadre Preferences.***

Outside of the home cadre ranking (which is a strategic ranking due to the insider priority), the serial dictatorship based New Mechanism is strategyproof. Hence we use discrete choice methods to understand the calculus behind the IAS officers' rank-order preferences for non-home cadres.

We have preference data for 122 Indian Police Service (IPS)—also amongst the elite, All-India Services that uses the same cadre assignment mechanisms—officers each rank-ordering 24 cadres data from the 2008 batch. Strategyproof preference data allows us to analyze the selection of the top 5 and bottom 5 preferences using conditional logits and the

[22]Quoting from Benbabaali (2008), "The sample is representative of the whole batch in terms of gender, rural/urban breakup, and administrative category (Scheduled Caste, Scheduled Tribe, Other Backward Class, General). To preserve the anonymity of the respondents, the exact year of the batch is not given, but it is one recruited between 2003 and 2006."

[23]Benbabaali (2008) recounts an interview where an IAS officer from Andhra Pradesh recounted his family's reaction to finding out he was allotted the Assam cadre: "When I told my mother that I was posted in Assam, she started crying. I asked her why. She said that the only time she heard about Assam was in a Telugu movie in which the hero punishes the villain by putting him in a train to Assam." Such reactions illustrate the intensity of these preferences and how they are rooted in cultural biases and (mis-)perceptions.

[24]See Appendix D for our measure of correlation across N rank ordered lists, a generalization of the Spearman rank correlation.

ranking criteria for the entire preference list using a rank-ordered logit (Table 4). As expected, civil servants positively reward cadres that are close by and those that are wealthier, have better health outcomes, and have better development capacity. Although proximity is of primary importance, at the top of their preferences civil servants care about how wealthy the state is, where as at the bottom, they rank states based on their development outcomes. These findings corroborate anecdotal evidence from interviews with IAS officers who mention that proximity places a key role in preference rankings, overall wealth and higher standard of living is preferred at the top, while development outcomes play a role in ranking the very bottom of the preference list.

Underlying the rank-order logit is a latent utility specification using which we can understand the relative weights civil servants place on these various dimensions. In such an analysis, it is imperative to consider the relative variability in the data for each of these dimensions. We find that a 1 standard deviation increase in Distance from Home State (of 381 miles) is equivalent to 1.48 standard deviations of percentage rural roads surfaced, 3.67 standard deviations in health index, and 4.74 standard deviations in per capita GSDP (Table 5 (3)). This suggests that proximity is by far the most valued covariate, followed by development and standard of living. When we compare the magnitudes from the conditional logit for the top 5 (Table 5 (1)) and bottom 5 (Table 5 (2)) we see how the effect of health index and GSDP per capita, respectively, lose importance, given the extremely high ratio of 1 standard deviation effects relative to distance. As an illustrative example of such ranking behavior, see Figure 14 for the cadre preferences by quartiles for IPS officers from Uttar Pradesh in 2008.

Using our estimated model, we also compute the average distance candidates are willing to travel to get a certain cadre relative instead of an average cadre (Table 7). Many bad cadres appear at the bottom of the list, e.g., candidates are willing to travel 837 miles to avoid Assam-Meghalaya over the average cadre.

4.3.4. *Analysis for Exam Topper Production by Cadre.*

Since there is an imbalance in the production of exam toppers by cadre, a priority given to insiders in the mechanisms, and a quality balance constraint, it is imperative to understand where exam toppers originate from. We analyze the data on the counts of exam toppers from different cadres using a Poisson regression. Although health index, population, and per capita income are positively correlated with number of exam toppers, literacy appears significant but with negative coefficient (Table 8). In fact, in India, comparatively, literacy rates are pretty high in the Northeast, from where there are very few successful exam toppers. And even the state with the highest literacy rates—Kerala—produces many exam toppers, but not nearly as many as states like Uttar Pradesh, Rajasthan, and Bihar. In these places, despite lower literacy rates in the broader population, there is a culture of valuing and aspiring for elite civil service positions. This further goes to show that the Civil Service Examination is competitive and selects from amongst the highest achievers.

The vast imbalance across cadres as to their ability to produce exam toppers is apparent from our estimated probability distribution functions shown in Figure 15.

4.3.5. *Impact of Imbalances on National Unity and Integration.*

In his famous speech to the Constituent Assembly in October 1949, India's first Home Minister and Deputy Prime Minister Vallabhbhai Patel, advocated for establishing the Indian Administrative Services as the "steel frame" of Indian administration. He said, "You will not have a united India if you do not have a good All-India Service which has independence to speak out its mind." Vallabhbhai Patel had advocated for the *All-India* service specifically designed to promote unity and integration. The structure of being allotted to a state cadre and then after a few years of service, being promoted or empanelled to the Centre, was so that these bureaucrats could experience the situation and progress of different states and report to the Centre as to their experiences.

By giving weight to the correlated preferences, the New Mechanism has not only caused a asymmetric distribution of talent, but has also led to an increase in homophily and regionalism. Our knowledge of the underlying mechanisms allow us to run the Old Mechanism on the New Mechanism era data for direct counterfactual comparisons. As seen in Figure 16, regional homophily—northerners staying in the north and southerners in the south—has jumped compared to that under the Old Mechanism. While homophily amongst just the southerners and just the northerners have both witnessed an increase with the New Mechanism, homophily amongst southerners has particularly sky-rocketed (Figure 17). The divide between northern and southern states is embedded in greater linguistic and cultural similarities within the two groups.[25] For example, Hindi is widely spoken and understood throughout most northern states, whereas it is not so common in the southern states. The average distance of the assigned cadre from the home cadre has also dramatically dropped with the New Mechanism and the variance of these distances across individuals has also fallen (Figure 18). These shifts clearly undermine the national integration purpose of the All-India Services.

4.4. **Who benefits and who loses from the mechanism change?**

By the zero-sum nature of the problem, though the New Mechanism adversely affects the bad cadres, it does benefit the good cadres. Good cadres tend to produce a sufficient supply of exam toppers to fill insider vacancies each year and these states also benefit from correlated preferences where they are ranked decently high and thus tend to attract higher scoring candidates competing for their vacancies in the New Mechanism.

How well do the candidates fare from the change in mechanism? Does the ability to express their full preference rank orders in the New Mechanism weakly benefit all candidates across exam ranks? The answers to these questions depend on the degree of correlation in preferences. Given the high correlation in preferences and the tendency to prefer cadres which are closer to home, our simulations suggest that the top three quartiles in terms of exam ranks are better off with the New Mechanism, at the expense of the bottom quartile (Figure 19 top row). However, if there was sufficiently low correlation in preferences, all quartiles of candidates could be better off with the New Mechanism (Figure 19 bottom row). The Old Mechanism's policy of not incorporating complete preference rank orders and imposing group rotations meant that top scorers could be assigned to the unanimously unpopular cadres and low scorers could be assigned highly popular cadres. Under the New Mechanism however, correlated preferences produce competition for the popular, highly sought-after cadres, and hence top quartile candidates fill up these vacancies, leaving bottom quartile

[25]The percentage of officers whose mother tongue matches the most popular language in their assigned cadre rose from 27.8% (4.4%) under the Old Mechanism (2005-07) to 39.4% (3.1%) under the New Mechanism (2003-13); an increase of 11.6*** percent.

candidates worse off.[26] Hence, the brunt of the change in mechanisms falls on the bottom quartile, which has mostly SC and ST candidates.

5. Consequences for State Capacity, Development, & Bureaucratic Performance

So far, our analysis has focused on variables that constitute the same information the UPSC and the central government have at the time of assignment. In this section, we evaluate whether these systematic imbalances documented above translate to imbalances in state capacity, developmental outcomes and bureaucratic performance.

The general responsibilities of IAS officers across their many postings, roles, and seniority ranks are threefold: i) maintaining law and order (district magistrate role), ii) revenue administration (district collector role), and iii) implementing development policy (chief development officer role). In Section 5.1, we emphasize role ii), which is a shared responsibility for most at early stages in IAS career. We use an empirical strategy exploiting the exogenous change in assignment mechanisms to assess the impact on tax collection and quantify the effect of exam rank on performance. Section 5.2 analyzes role iii) which was taken on during the transition from the Indian Civil Services under British rule to the Indian Administrative Service under independent India. We estimate the effect of the change in mechanism on the Human Development Index. We are then able to use our estimates to evaluate counterfactuals such alternative affirmative action policies and matching mechanisms. In Section 5.3, we consider other imbalances caused by the change in mechanism, on characteristics that correlate with bureaucratic performance, corroborated by results from the existing empirical literature.

5.1. **Impact on State Capacity: Tax Revenues.**

The change of cadre allocation mechanisms in 2008 gives us a clean, exogenous shock to the assignment of IAS officers to state cadres. Since later assignments to districts, transfers, and promotions are not formulaic and involve ministerial involvement (Iyer and Mani (2015)) and career trajectories and specializations within the IAS are vastly different by individuals(Ferguson and Hasan (2013)), empirically quantifying the long-term effect on development outcomes and bureaucratic performance is difficult. However, the first entry-position of IAS officers across all state cadres is that of Assistant District Collector/Magistrate.[27] Hence all IAS officers start their careers with the same primary job responsibility: revenue administration.[28] District Collectors/Magistrates are in charge of collecting various categories of own-tax revenue (income tax, agricultural income tax, irrigation dues, sales tax, excise duties, etc.), maintaining land records, and hearing appeals in revenue cases in their capacity as District Magistrates. Thus given these institutional features of the IAS, we measure the

[26] Understanding these heterogeneous effects can also highlight which coalitions might have stood for/against the endogenous change in the mechanism. Thakur (2019) studies this issue of stability of the matching mechanism as an endogenous institutional choice. Such analysis speaks to the economics and organizational behavior literature on theories of endogenous change in institutions; for example, Knott and Miller (1987).

[27] Early career postings in revenue management include Assistant District Collector, Additional District Collector, Assistant District Magistrate, Additional District Magistrate, Sub-Divisional District Officer, and Sub-Divisional Magistrate.

[28] Later on in their careers, some IAS officers may be transferred or promoted within revenue administration to higher posts like District Collector/Magistrate, while most are assigned to posts with responsibilities other than revenue administration.

impact of the change in mechanism on state capacity using tax revenue data. This uses the cleanest exogenous variation we have at the state level due to the change in mechanism and focuses on a measure that captures all IAS officers' commonly shared, initial job responsibility of tax collection.

We use state-level revenue data from 12th and 13th Finance Commission Reports covering fiscal years 2005 to 2015. The IAS batch that qualifies under say the 2008 cycle, goes through mandatory training for one year (2009-10), and begins to work in 2010. Thus, the entrants from the New Mechanism start work in 2010 and start affecting revenue collection from fiscal year 2010-2011 onwards. Because of the skew in quality of assigned IAS officers under the New Mechanism, we expect the good and bad cadres to diverge in tax collection performance from fiscal year 2010-11 onwards. The zero-sum nature of the assignment procedure means that the divergence represents the joint effect of lower quality bureaucrats going to bad cadres and higher quality bureaucrats going to good cadres. Moreover, we expect this divergence to grow over time as a larger fraction of the stock of existing bureaucrats is replaced by new entrants from the New Mechanism. Own tax revenues (including income tax, excise duties, and land revenue, which fall under District Collector/District Magistrate's jurisdiction) seem to move in line with our expectations (Figure 20 top left and bottom). Non-tax revenues (such as interest receipts and revenue from public sector companies and public services), which is a placebo variable the IAS officers cannot control, should not show such a divergence (Figure 20 top right).[29] Since good and bad cadres have different pre-trends, instead of using difference-in-difference, we estimate the impact of the New Mechanism using a structural break empirical strategy. Table 9 shows that the change in linear time trends due to the New Mechanism is Rs. 1336.6 crore ($206 million) higher in good cadres relative to bad cadres, with standard error Rs. 280.6 crore. The effect on the placebo non-tax revenues, is not significant.[30] Alternatively, in similar spirit, we can de-trend each cadre by its Old Mechanism years linear trend, and run a difference-in-difference on the de-trended revenues (see Figure 22)[31]. This gives us comparable estimates of Rs. 5330.9 crore ($820 million) lower own tax revenue[32] for bad cadres relative to good cadres, and insignificant effect on the placebo non-tax revenues (see Table 11).[33] For robustness of revenue analysis in logged terms, see Table 25 and Figure 57 in Appendix H.

Furthermore, using the change in mechanism as an instrument for the average quality of the set of IAS officers assigned to a cadre,[34] we find that 1 lower exam rank corresponds to Rs. 85.11 crore ($13 million) lower own tax revenue (Table 10 second column). When trying to estimate the effect of a state's average exam rank on own tax revenue, a simultaneity issue arises. As shown above, states with higher revenues tend to produce more exam toppers and

[29]The jump in Figure 20 appears because of Maharashtra and Haryana. See Figure 21 for robustness excluding these cadres.

[30]See Table 24 for robustness checks excluding Haryana and Maharashtra. All results for non-tax revenue show up as insignificant regardless of whether you include or exclude either or both states.

[31]The jump in Figure 22 appears because of Maharashtra and Haryana. See Figure 23 for robustness excluding these cadres.

[32]The structural break strategy gave a difference in linear trends of Rs 1336.6 crore, which translates to New Mechanism treatment effect of 1336.6*(1+2+3+4+5)/5= Rs. 4009.8 crore due to 5 ("post-treatment") years under the New Mechanism.

[33]See Table 24 for robustness checks excluding Haryana and Maharashtra. All results for non-tax revenue show up as insignificant regardless of whether you include or exclude either or both states.

[34]The first stage is the difference-in-difference in average exam rank across good and bad cadres due to the change in mechanism we estimate in Table 2.

candidates tend to favor states with higher revenues in their cadre preferences. As a result, better exam scorers are disproportionately more likely to be assigned to high-revenue cadres. Moreover, since state's average exam rank is a noisy measure of the latent quality of the set of candidates assigned, we might also have errors in variables. To alleviate this endogeneity problem, we use the exogenous change in cadre allocation mechanisms as an instrument, that affects revenues only through its effect on the set of IAS officers assigned to a state and not through any other channels. In this exercise, the state's average exam rank is used as a proxy for the latent quality of the set of candidates assigned and the object of interest is identifying the effect of changing the latent quality of the set of officers assigned on own tax revenues. Namely, if a state were to swap all its officers for those ranked immediately above them, the state's own tax revenues would increase by $13 million. To put this estimate into perspective, the average own tax revenue across state cadres in 2015 was $4.2 billion.

Thus, exam rank appears to be indicative of bureaucratic performance.[35] Our estimates help quantify and legitimize the quality dimension as a potentially important dimension to target global balance across state cadres. Moreover, using this estimate, we can now run back-of-the-envelope calculations for revenues under counterfactual mechanisms and different affirmative action policies. For example, from Table 12 we see that the forgone own tax revenue due to reservation policies in 2015 was around Rs. 9,250 crore ($1.4 billion).[36] To put this in perspective, the total own tax revenue for all these states in 2015 was $118 billion. Similarly, we can quantify the yearly forgone own tax revenue due to each quota category: for example in 2015, Rs. 2,290 crore ($352 million) due to ST reservation, Rs. 5,128 crore ($789 million) due to SC reservation, and Rs. 1,891 crore ($291 million) due to OBC reservation (Table 12).

5.2. **Impact on Development: Human Development Index.**

IAS officers are the implementation arm of the government for many policies such Mahatma Gandhi National Rural Employment Guarantee Act (MNREGA), education policies, infrastructure projects, etc. However, their development roles are specialized across different postings and each IAS officer is given different jurisdictions, specializations, and spheres of influence. Hence, although we exploit the same state-level variation as a result of the mechanism change in this section, we believe the micro-foundations and causal path for tax revenue effects found above are better identified. We find that as a result of the New Mechanism, bad cadres have a 0.05 lower HDI compared to good cadres (Table 13). Since HDI is not calculated on a very regular basis, although the difference-in-difference specification seems motivated by convincing parallel trends in Figure 25, we interpret this finding with some caution.

5.3. **Impact on Development Outcomes & Bureaucratic Performance using Existing Literature.**

Bertrand et al. (2015) find that exam scores predict their survey-based perceived bureaucratic effectiveness score, so the skewed distribution in Civil Service Examination scores by cadre resulting from the New Mechanism is troubling in and of itself. Furthermore, they

[35]Existing literature has also established a positive effect of exam rank/score on perceived bureaucratic effectiveness (Bertrand et al. (2015)) and decreased likelihood of politicized transfers (Iyer and Mani (2012)).

[36]The counterfactual calculations averages exam rank across all candidates, and replaces all N_q candidates for each quota category q, with the N_q highest exam scorers who did not qualify due to affirmative action policies.

find that officers who are older and enter with a large cohort within the assigned state exhibit lower perceived bureaucratic effectiveness.[37] They argue that this is because older candidates face longer delays for promotions when they are in larger cohorts and given the fixed retirement age, might anticipate lower chances of career advancement and exert less effort. We find that with the New Mechanism, bad cadres on average get candidates who are 0.47 years older than those assigned to good cadres (Table 14). This is driven by the positive correlation between age and exam rank, i.e., older candidates tend to perform worse on the exam. Hence, bad cadres will tend to get IAS officers who are locally perceived by politicians, businesses, NGOs, and other civil servants to be less effective.

Iyer and Mani (2015) find that high ability officers (top 20 by exam rank) are transferred 2.2 percentage points less frequently after the election of a new chief minister.[38] Figure 26 shows that while the Old Mechanism was allocating between 25-30% of top 20 scorers to bad cadres,[39] this has dropped drastically to near 0% under the New Mechanism. Hence bad cadres will have IAS officers facing increased posting variability in a response to political changes under the New Mechanism.

Bhavnani and Lee (2015) suggest that an increase in the proportion of insiders from the mean by one standard deviation (0.27) leads to a 4.6% increase in proportion of villages with high schools (i.e., public good provision). Embeddedness has no effect on high schools in districts where there is low literacy (47% of districts in India have less than 20% literacy) or where there is low newspaper circulation (66% of districts have high enough circulation), hence the capacity for accountability is lacking. For the district with the median number of villages, this translates to 1 additional school per year (for mean district would translate to adding 4 schools per year). Moreover, Hjort et al. (2015) find that local language proficiency predicts higher value-added IAS officers as measured by worse project outcomes, lower luminosity, and decreased chance of future empanelment. Moreover, they find that local language proficiency correlates positively with being an insider. Comparing the difference between insiders requested and insiders assigned as a percentage of total requests, we see that because the bad cadres tend to produce fewer exam toppers, they face a shortage of insiders (Figure 27). Hence, bad cadres might have lower public good provision and relatively lower value-added bureaucrats.

Ferguson and Hasan (2013) find that training, education, and specialization has career benefits both in the short run (promotions to Centre) and the long run (empanelment). The 2008 and 2009 batches have weak but negative correlations of -0.14 and -0.37 between being assigned a bad cadre and the average number of trainings completed. This might suggest that bad cadres are assigned less capable candidates who invest less in developing expertise and thus have a lower likelihood for promotion.

6. The Scope For Market Design

[37]The IAS cohort size has consistently increased from 87 vacancies in 2005 to 180 vacancies in 2015. Furthermore, the upper age limits and maximum number of attempts at the UPSC exam have also consistently been relaxed in recent years. Current eligibility criteria limits ages 21-32 for General Category with a maximum of 6 attempts, ages 21-35 with a maximum of 9 attempts for OBC Category, and ages 21-37 with unlimited attempts for SC/ST Category and candidates from Jammu and Kashmir.

[38]Given that the average increase in the likelihood of transfer following an election turnover is 4.9%, this is a significant decrease by around 47%. To put into perspective, Iyer and Mani (2015) find that the baseline transfer probability for an IAS officer in any given year is 53%.

[39]Around 30% would be natural as 7 out of 24 cadres we have identified as the under-performing bad cadres.

6.1. **Addressing Correlation in Preferences.**

As we have shown above, many global imbalances arise due to candidates having correlated preferences over cadres and a seemingly shared consensus over which cadres are desirable and which are not. These preferences can be nudged either implicitly or explicitly.

6.1.1. *Implicitly Nudging Candidates' Preferences: bonuses, perks, career opportunities.*

Implicit nudges can be structured in various ways. Firstly, IAS officers working in distressed areas can be compensated with an income bonus, better facilities, or increased perks.[40] This will not only attract insiders from bad cadres to stay in their home state, but also attract outsiders to rank distressed cadres higher in their preference lists. Secondly, the attractiveness of bad cadres can be uplifted by enhancing career opportunities. For example, the Centre can allow a higher proportion of officers to be eligible for deputation, or seniority restrictions for promotions and empanelment can be relaxed relative to good cadres so that career advancement is quicker in bad cadres.

6.1.2. *Explicitly Restricting Candidates' Preferences: 2017 Mechanism and Strategyproofness.*

The government can explicitly mandate restrictions over how candidates are allowed to express their preferences over state cadres. Candidates can be forced to rank fewer preferences or rank coarser preferences such as preferences over regions containing many state cadres. However, such direct restrictions on preferences are known to often render the mechanism non-strategyproof.

Concerned by the growing regionalism (Section 4.3.5) which undermined the national integration purpose of the All-India Services, the UPSC announced a revised cadre allocation policy starting for the 2017 batch onwards.[41] The 2017 Mechanism is the New Mechanism discussed at length in this paper, but with an added preference order restriction for the civil servants when ranking the cadres. We describe the preference order restriction here, show why such a restriction renders the system non-strategyproof, and instead use Deferred Acceptance with regional mobility soft constraints to achieve the intended regional mobility while maintaining strategyproofness.

The 2017 Mechanism groups the cadres into 5 zones by region:

(1) Zone I: AGMUT, Jammu and Kashmir, Himachal Pradesh, Uttarakhand, Punjab, Rajasthan and Haryana
(2) Zone II: Uttar Pradesh, Bihar, Jharkhand and Odisha
(3) Zone III: Gujarat, Maharashtra, Madhya Pradesh and Chhattisgarh
(4) Zone IV: West Bengal, Sikkim, Assam-Meghalaya, Manipur, Tripura and Nagaland
(5) Zone V: Telangana. Andhra Pradesh, Karnataka, Tamil Nadu and Kerala

Each candidate must first to rank the 5 zones in order of preference 1:5, and then, rank their preference amongst cadres within each zone separately. Then, the final preference order for the candidate rotates across the 5 zones in order of within zone preference: i.e.,

(1) 1st preferred cadre in 1st preferred Zone
(2) 1st preferred cadre in 2nd preferred Zone
(3) 1st preferred cadre in 3rd preferred Zone

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[40]See Dal Bo, et al. (2012) for the effects of increasing wages for bureaucrats in Mexico on quality of applicants. See Agarwal (2017) for estimating effects of wage increases at rural hospitals on willingness to match to rural hospitals, resident quality, and unfilled rural hospital vacancies.

[41]See https://easy.nic.in/csePlus/Docs/cadrepolicy2017.pdf for the official 2017 policy.

(4) 1st preferred cadre in 4th preferred Zone
(5) 1st preferred cadre in 5th preferred Zone
(6) 2nd preferred cadre in 1st preferred Zone
(7) 2nd preferred cadre in 2nd preferred Zone
(8) ...

There are two other important caveats. First, to qualify for an insider vacancy, the candidate must rank the Zone containing his home cadre as his 1st choice, and must rank his home cadre as his 1st choice within that Zone. Second, not ranking cadres or zones is treated as being indifference amongst the un-ranked cadres or zones.

The New Mechanism is not strategyproof because of the Insider priority, yet in the subset of non-home state cadres, ranking is strategyproof (Section 6.3). The 2017 Mechanism is the same as the New Mechanism with the added preference restrictions described above. However, these preference restrictions render the mechanism non-strategyproof, even amongst the subset of non-home state cadres.

With the simple numerical example below, we illustrate two points:

(1) The 2017 Mechanism is not strategyproof for cadre preference within a zone (we call "intra-zonal strategyproofness")
(2) The 2017 Mechanism is not strategyproof for zonal preferences across zones (we call "inter-zonal strategyproofness")

Consider the 2017 Mechanism for 4 cadres $\{a, b, c, d\}$ divided into two zones $\{Z_1, Z_2\}$ with $\{a, b\} \in Z_1$ and $\{c, d\} \in Z_2$. The true utility value for cadre i is denoted v_i. We consider $v_a > v_b > v_c > v_d$. Let p_i denote the probability of getting into cadre i. *Inter-zonal strategyproofness* would imply $Z_1 \succ Z_2$, since each cadre in Z_1 dominates each cadre in Z_2. Moreover, *intra-zonal strategyproofness* implies $a \succ b$ in Z_1 and $c \succ d$ in Z_2.

We show that there exists probabilities p_i and valuations v_i such that the optimal rankings are $Z_2 \succ Z_1$ (violating inter-zonal strategyproofness), and $c \succ d$ in Z_2 and $b \succ a$ in Z_1 (violating intra-zonal strategyproofness). Consider the following example:

- c is the home cadre for this candidate
- $v_a = 1.9$, $v_b = 1.8$, $v_c = 1.7$, and $v_d = 1$
- $p_a = .3$, $p_b = .5$, $p_d = .7$, $p_c = \begin{cases} .9 \text{ if ranked 1st in } Z_2 \text{ and } Z_2 \text{ ranked first,} \\ 0 \text{ otherwise} \end{cases}$

The logic of the numerical example is that Zone 1 is preferred to Zone 2 by dominance, however, the candidate's home cadre c for which he has insider priority (hence high p_c) is in Zone 2. Although the candidate prefers both cadres a and b to his home cadre c, he optimally ranks c first overall due to the insider priority. Namely, if c is not ranked 1st in its zone Z_2 and if Z_2 is not ranked as the most preferred zone, the candidate cannot get his home cadre. Hence, he ranks $Z_2 \succ Z_1$, violating inter-zonal strategyproofness. Moreover, although $v_a > v_b$, since $p_b > p_a$, to avoid failure and get the worst cadre ($v_d << v_b$) with a high probability of 0.7 (since it is the worst cadre, no one wants it, so the candidate will get it with high probability if he ranks it), the candidate would rather get b with higher probability and avoid getting d, instead of getting a with smaller probability with greater risk of getting the bad outcome d. This violates intra-zonal strategyproofness as the stated preference is $b \succ a$ in Z_1.

This example abstracts away from an equilibrium being played across many candidates, differences in information across candidates, etc. However, it simplifies the general environment to its core, underlying strategic problem: given a set of utilities v_i and probabilities (beliefs) of getting in p_i for each cadre i, a single player (IAS candidate) reports his preferences over zones and his preferences over cadres within each zone.

To establish a benchmark on how susceptible the 2017 Mechanism is to strategic behavior, we assume all agents truthfully report their true preferences and then consider how many individuals have an incentive to strategically deviate. Figure 28 shows how many more preferred cadres can be achieved with strategic reporting for each individual in IPS 2008 batch.

We show that regional balance—which is the motivation behind the 2017 policy—is attainable through soft constraints (Ehlers et al. (2014)) where seats are prioritized for candidates from different regions. Table 16 shows this by simulation and compares Deferred Acceptance with regional and insider constraints with both the 2017 Mechanism and 2008 New Mechanism. Deferred Acceptance with regional and insider constraints can get sizeable movement across regions, even more than 2017 Mechanism with naive truth-telling. Moreover, this mechanism is strategyproof and the amount of regional movement desired can be adjusted with different soft constraint priorities. Both Deferred Acceptance with regional and insider constraints and the 2017 Mechanism outperform the 2008 New Mechanism in terms of regional mobility and quality balance. The 2008 New Mechanism discourages regional movement to and from Zones and produces a vast imbalance in exam rank across Zone 4 (which has most of the bad cadres) and the other Zones.

6.2. **Addressing the Skew in Origin of Exam Toppers.**

6.2.1. *Grouped Cadres.*

The choice of certain states to be collectively represented as a single administrative unit ("joint cadre") provides some interesting case studies. In most instances, the grouping (or the lack thereof) seems arbitrary, yet it is a result of complex legislation arising from intricate political compromises:

(1) The Northeastern Areas Reorganization Act of 1972 created three separate states in the northeast: Meghalaya, Manipur, and Tripura. Manipur and Tripura were combined to form a joint cadre, which lasted until 2014, after which each state has been represented individually as a distinct cadre.
(2) Meghalaya was carved out of the existing state of Assam in 1972, but the two states are represented as the joint cadre Assam-Meghalaya.
(3) The Northeastern Areas Reorganization Act of 1972 also added Arunachal Pradesh and Mizoram to the AGMUT cadre, which also consisted of seven other Union territories (Delhi, Chandigarh, Andaman and Nicobar Island, Lakshadweep, Goa, Daman and Diu, and Dadra and Haveli). Hence, the AGMUT cadre is a large conglomerate composed of some (but not all) states from the northeastern bloc, the capital city, an ex-Portuguese colony, and some coastal towns and islands. Each of these territories was liberated and had obtained statehood at different times.
(4) On the other hand, recently formed new states are individually represented as distinct cadres. In 2000, in an attempt to break large states in central India, Chhattisgarh was carved out of Madhya Pradesh, Jharkhand from Bihar, and Uttarakhand from Uttar Pradesh. Furthermore, in 2014, Telangana separated from Andhra Pradesh due to internal movements calling for separation.

From the matching theory perspective, these groupings produce certain asymmetries and cross-subsidizations.

Firstly, exam toppers often tend to originate predominantly from certain states/territories in each of these joint cadres (Figure 31). From 2005-2015, 74% of AGMUT exam toppers were from Delhi, 73% of Assam-Meghalaya exam toppers were from Assam, and 87% of Manipur-Tripura exam toppers were from Manipur. There are also relatively large asymmetries in exam toppers from the new states (Uttarakhand, Jharkhand, and Chhattisgarh) relative to their counterparts (Uttar Pradesh, Bihar, and Madhya Pradesh) as seen in Figure 32. It turns out that the ratio of exam toppers (i.e., potential insiders) relative to vacancies for a given cadre is an important determinant of average exam rank (due to the priority for insiders). The low ratio in Chhattisgarh (22%) might partly explain why that new state does particularly worse compared to other new states like Jharkhand (71%) and Uttarakhand (52%) (Table 15). Given the 2:1 targeted ratio of outsiders to insiders, 33% is a conservative benchmark below which the cadre will most certainly not be capable of filling insider vacancies.

Secondly, there are cross-subsidizations in bureaucratic quality as well. Candidates from mother states have lower average exam ranks than those from the new states (Figure 32). Similar patterns arise with Delhi and Chandigarh in AGMUT and Assam in Assam-Meghalaya (Figure 33).

Finally, we can observe the impact of the splitting joint cadres with the Manipur-Tripura split and the separation of Telangana from Andhra Pradesh in 2014 (Figure 34). It is important for the grouped cadres to have poorly performing state(s) be bolstered via cross-subsidization by relatively high performing state(s). Manipur and Tripura are both relatively poor performing states and hence their grouping into a joint cadre does not provide much gain to either. On the other hand, Andhra Pradesh is a high performing state and the Telangana region lost drastically in terms of quality of bureaucrats when it separated.

The designer/planner having control over how to define an entity in the matching problem (i.e., the state cadre is an administrative unit), is indeed a unique feature to this political economy setting, in comparison to most matching applications. As a policy recommendation, it can be beneficial from a central planner's perspective, to group poor performing states (i.e., bad cadre) with high performing states (i.e., good cadres) and have the poor performing states benefit from cross-subsidization with more insiders of a higher quality. However, grouping multiple poor performers together is often times not beneficial for any of the states. From both a social welfare and matching perspective, there may be certain natural groupings like combining new states with their mother states; however, whether or not certain groupings would be politically viable is beyond the scope of this paper. It is imperative that such decisions of creating joint cadres be made after careful statistical simulations, because grouping cadres and expanding their pool of insider candidates can adversely impact other cadres who now have a small pool of outsiders.

6.2.2. *Impact of Cadres Reporting Vacancies & UPSC Choosing Candidates.*
So far, we have taken two inputs as given: the list of vacancies formed by the cadres and the list of candidates narrowed down by the UPSC for the IAS. In this section, we consider the consequences of these input choices.

The UPSC rules target the 1:2 ratio of insiders to outsiders and Indian law on affirmative action mandates 15% seats reserved for SC, 7.5% for ST, and 27% for OBC. Within these constraints, how exactly state cadres form their final roster of vacancies is not clear, but may be potentially consequential. In the Old and New Mechanisms, swaps ensure that shifting vacancies amongst insider categories has no effect if the number of candidates willing to be insiders are at most the total number of insider vacancies because swaps give all insiders a chance. In the Old Mechanism, swaps also require outsider vacancy in the quota category being swapped in to facilitate the exchange. However, if there are more candidates willing to be insiders than there are insider vacancies overall, who is allocated to their home cadre depends on which quota category is given more vacancies.[42] For example, shifting vacancies from General insider to SC/ST insider and OBC insider will lead to better performance on both the insider and the quota dimension if the cadre has more General insider vacancies than it does candidates and it has more OBC, SC, and ST insider candidates than it has vacancies. However, to the extent SC, ST, and OBC candidates tend to have lower exam ranks, this will affect the quality of assigned candidates. Hence, by shifting vacancies within a state, both the quality of assigned candidates and the distribution of quality across cadres changes. States can prioritize certain quota groups in getting in by increasing the number of vacancies in that insider quota group. Although this power could be misused,[43] it is important to bring to attention from a matching theory perspective.

In constructing the final list of qualified candidates to match the number of vacancies, the UPSC has chosen to prioritize exam rank and quota, but not embeddedness (i.e., insiders).[44] To address the paucity of exam toppers from bad cadres, the government can establish civil service training centers, reserved seats,[45] or relaxed qualification requirements for candidates from bad cadres.[46] If the UPSC goes further down the exam rank of candidates to get exam toppers from home states which are not represented in the current lists, the shortcoming faced by bad cadres in placing insiders can be relaxed at the cost of lower exam ranks. In light of Bhavnani and Lee (2016), Vaishnav and Khosla (2016) suggested experimenting with increasing the proportion of insiders. If such policy recommendations are to be taken seriously, the roster of candidates must be adjusted to overcome these asymmetries in how candidates from different cadres perform. In other words, the trade-off associated with making the insider constraints binding, is admitting candidates with lower exam rank.

6.3. **An Approximate Ranking of One-Sided Cadre Allocation Mechanisms.**

Despite the complex underlying correlations in the data and the fact that vacancies and exam toppers change year by year, we can form an *approximate* ranking of one-sided mechanisms by analyzing the extent to which they address the correlations in the data (Figure 3). The underlying correlations which mechanisms should address are 1) the asymmetric regional

[42] Similar effects occur in two-sided matching with soft constraints (Section 6.4.1).

[43] For example, there have been allegations during the Old Mechanism years (1984-2007)— when cadres reported their vacancies after seeing the final list of candidates— that vacancies were strategically tampered with to favor certain candidates. From 2008 onward with the New Mechanism, cadre vacancies are made available prior to the list of candidates, so this point of contention has become moot.

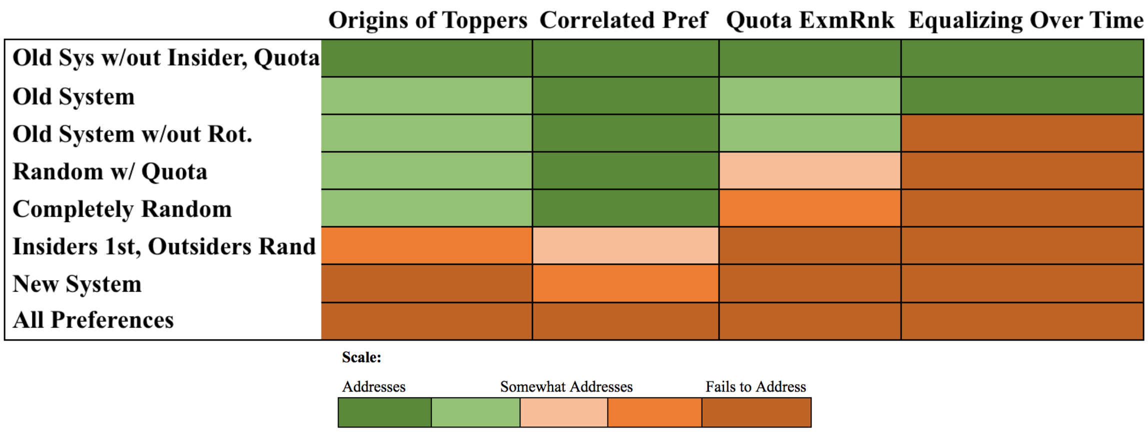
[44] From the overall list of exam toppers, those who opt for the IAS are separated out. Next, based on total vacancies by quota type, the UPSC determines exam rank cutoffs for ST, SC, OBC, and General categories. There are always weakly more SC, ST, and OBC candidates then there are vacancies, because quota candidates who qualify under the General category count against the General category and not the quota category. However, there is no attempt made to meet insider vacancies.

[45] For example, in the Pakistan Administrative Service, recruitment via Civil Service Examination is done using provincial quotas to ensure regional representation balance in the civil service.

[46] For example currently, candidates from Jammu and Kashmir have a relaxed age limit of 37 (same as SC/ST category candidates) and are allowed unlimited attempts at the Civil Services Examination.

representation amongst exam toppers, 2) the correlation in preferences of candidates, 3) the tendency of quota candidates to have lower exam ranks, and 4) the ability of the mechanism to equalize quality over time. The following discussion illustrates the incremental effects of various design features of the mechanisms.

Figure 3. Approximate ranking of one-sided mechanisms: An approximate ranking of one-sided mechanisms and the extent to which they address the correlations in the data: origins of exam toppers, correlated preferences, quota candidates having lower exam ranks, and equalizing quality over time.



Let us start with the Old Mechanism (labelled the "Old System") which addresses many of the correlations in the data. First, the only input from the candidates is whether or not they are willing to be an insider, hence the correlation across the entire rank order of preferences is altogether avoided. Second, balance in assigned quality across time is guided by the rotating groups and 1:24 cycles. Finally, though asymmetric regional representation amongst exam toppers and lower exam rank amongst quota candidates cause some imbalances because of the priority given to insiders and quota candidates, these are alleviated by the 1:24 cycles.

If we keep the structure of the Old System but ignore insider-outsider distinctions and quota constraints (labeled "Old Sys w/out Insider, Quota"), we would do away with the asymmetries arising from origin of exam toppers and lower exam rank amongst quota candidates in the Old Mechanism. This underscores how targeting balance across the embeddedness and quota dimensions is indeed a constraint.

On the other hand, if we consider the Old Mechanism without rotating groups across years (labeled "Old System w/out Rot."), the mechanism would not attempt to equalize quality across cadres over time. The rotation of group orders alternates the comparative advantage of being given higher priority in the 1:24 cycle every 4 years.

Next, eliminate the 1:24 cycles and consider randomly allocating candidates within quotas (labeled "Random w/ Quota"). While the 1:24 cycle imposed structure to prevent bunching on quality in certain cadres, this mechanism admits for such bunching and introduces the possibility of multiple lower quality candidates being randomly assigned to one cadre. Hence the performance on the quota-exam-rank dimension is slightly worse.

Subsequently, if we assign candidates randomly (labeled "Completely Random"), we can end up with the low ranked quota candidates being bunched together in certain cadres by chance. In the Random within Quota mechanism, the low ranked quota candidates were at least being distributed based on the roster of vacancies, but now even this leveling effect is removed, leading to higher variability amongst average exam rank across cadres.

Now if we go through the candidates by exam rank, first assign insiders when there is a corresponding insider vacancy in their category, then implement swaps as per the New Mechanism, and finally randomly assign all remaining candidates as outsiders (labeled "Insiders 1st, Outsiders Rand"), this mechanism introduces the correlation coming from the origin of exam toppers because insiders are given preferential treatment. Furthermore, the correlated preferences problem can be exacerbated if candidates from bad cadres would rather prefer a random outsider assignment relative to an insider position. Finally, random outsider assignment continues to allow for bunching of poor exam rank candidates.

Further tweaking the mechanism to first go through insiders and swaps, and then go by exam rank through the preferences of outsiders, we get the New Mechanism (labeled "New System"). This further exposes the mechanism to correlated preferences amongst outsiders who we were previously being assigned randomly. Moreover, the origin of exam toppers (and hence their preferences) further affects the mechanism because exam toppers coming from the same state tend to have even more correlated preferences.

Finally, we can consider a mechanism where all candidates are simply ranked by exam score and allowed to choose based on their ranked preferences, as in a Serial Dictatorship where order is exam rank (labeled "All Preferences"). This further exacerbates the correlated preferences problem as, the mechanism introduces correlated preferences amongst even those who would have otherwise have opted for insider positions in the previous mechanism.

This approximate ranking we derive is reflected in the t-statistic comparisons (Figure 29)[47] and mean/variance comparisons (Figure 30) between these simulated alternative mechanisms and the actual assignment data. Since the Old Mechanism with rotation (black with star line) rotates across different group orders of the Old Mechanism without rotations (yellow curves), the gain from the rotations becomes evident when we consider the average exam rank of the allotted candidates for each cadres across years in our simulations. Across 2007-2013, with rotation the average exam rank across cadres is distributed with mean 95.9 and variance 1419.4. Without rotation, the distribution is mean 95.8 and variance 3313.9. Furthermore, if we take the Old Mechanism without insider-outsider or quota restrictions (red with star line), we get distribution with mean 94.2 and variance 1389.1. Hence, the group rotations in the Old Mechanism work to equalize average exam rank across cadres by prioritizing different states in the 1:24 cycles over time.

Rather than advocating for a certain mechanism to be implemented, the purpose of this approximate ranking is to show incrementally how to get from the Old Mechanism to the New Mechanism, and highlight how certain features of the mechanisms address (or fail to address) the underlying correlations in the data. In the process, we also highlight some important trade-offs for the mechanism designer. First, given that preferences are correlated, the market designer must decide how much weight to give to candidates' preferences. The

[47]The t-statistic is defined by $t = \frac{\mu_{actual} - \mu_{simulated}}{\sqrt{\frac{\sigma^2_{actual}}{24} + \frac{\sigma^2_{simulated}}{24}}}$, where $\mu_{actual}, \mu_{simulated}$ are the across-cadre averages of average exam rank of assigned candidates by cadre, and the $\sigma^2_{actual}, \sigma^2_{simulated}$ are the across-cadre variances of average exam rank of assigned candidates by cadre.

more weight the mechanism assigns, the more lopsided allocations tend to be. For example, the Old Mechanism pays minimal heed to candidates' preferences while the New System takes preferences very seriously. Second, given asymmetric regional representation amongst exam toppers, the designer must consider the priority given to insider positions in light of the fact that certain states, like the bad cadres, will not be able to fill insider vacancies. The comparison between Completely Random mechanism and the Insiders 1st, Outsiders Random Mechanism shows this difference most starkly. Prioritizing insiders first, comes at the cost of not assigning bureaucratic quality as evenly. Finally, given that quota candidates tend to have lower exam rank, the designer must balance the distribution of quota candidates. As we see with the Random with Quota and Completely Random mechanisms, the cadre's vacancies for quotas are actually beneficial in disciplining the mechanism to uniformly distribute quota candidates. Nevertheless, when comparing the Old Mechanism with the Old Mechanism without insider and quota constraints, we see that the equitable bureaucratic quality can sometimes be improved by relaxing quota priorities.

6.4. **Two-Sided Cadre Allocation Mechanisms.**

Over the course of their careers, IAS officers are assigned to many different positions ranging from from being in charge of animal husbandry and agricultural policy (where scientific and technical understanding might be useful), managing land revenue and district administration (where commerce or finance degrees might come in handy), working with NGOs and government programs to administer rural development projects (where policy or government school degrees can be beneficial), working closely with tribal areas (where history, politics, and cultural knowledge might be imperative), to setting higher education policy and human resource management (where science and engineering degrees might be useful). In fact, the government labels different IAS posts by their specializations such as Youth Affairs and Sports, Land Revenue Administration and District Management, Finance, Transport, Tribal Welfare, Social Justice and Empowerment, to name a few. Clearly, increasing specialization in these areas of management and administration suggests that matching IAS officers to posts based on their education, work experience, and technical training might be useful.

The IAS was based on the British system of Indian Civil Services from the colonial era. This system was based on a generalist philosophy: an IAS officer is a bureaucrat who regardless of his educational background, work experience, and skills, should be able to effectively thrive in any post. However, the empirical literature on bureaucratic performance says otherwise. Specialization, advanced education, and local language proficiency predict bureaucratic success both in terms of higher likelihood of promotion and better outcome performance (Ferguson and Hasan (2013), Hjort et al. (2015)).

IAS officers have diverse education backgrounds ranging from medical doctors and MBAs to engineers and economics PhDs. Thus, there seems to be a good case to be made from having cadres express preferences over candidates based on the skills their vacancies require. Moreover, there are many languages spoken across India, but often concentrated within states. In fact, state boundaries in India were defined by the prevalent language spoken in the region. Hence cadres might have preferences over candidates based on their mother tongues and languages spoken. By also incorporating cadre preferences over candidates, the matching becomes two-sided.

Although we believe that matching based on education, skill, and specialization is a first order concern, to minimize our set of assumptions in our two-sided matching simulation exercise, we focus here on local language proficiency. We use the 2001 Census data as reported in the 50th Report of Commission for Linguistic Minorities in India (2013), which documents the most commonly spoken languages by state. We assume cadre preferences over candidates are lexicographic with the first dimension being mother tongue matching local language spoken (in order of popularity) and the second dimension being exam rank. In reality, we expect that cadre preferences will be weighting many variables: exam rank, education, age, local language proficiency, and work experience. Our simulated preferences are meant to be a crude algorithmic approximation of the cadre's preferences over candidates, focusing just on the language dimension.

In Figure 35, we run the Gale-Shapley Deferred Acceptance mechanisms with candidates proposing (Right) and cadres proposing (Left) without paying heed to quota or insider-outsider constraints.[48] We vary the simulation assumptions on candidate's preferences: (1) "Block:" want to be insider, followed by random within block of good cadres, followed by random with block of bad cadres. (2) "Res3:" same as Block, but force every 3rd choice to be from bad cadre group (assuming truthful revelation). (3) "Uncorr:" want to be insider, followed by uncorrelated preferences over remaining cadres. (4) "Close:" cadres in order of closest distance from home state's capital city. The t-statistic comparisons indicate that such two-sided matching produces outcomes that lie mostly between the Old and New Mechanisms in terms of quality distribution imbalances.

Namely, introducing two-sided matching can also help remedy the correlation in preferences feeding through one-sided markets. How much of the correlation in preferences of candidates is 'undone' by incorporating cadre preferences, depends on how correlated cadre's preferences are and which side proposes. For example, with the candidate-proposing mechanism, the Uncorr and Res 3 preferences for the most part dominate the Block and Close preferences as for quality distribution imbalance. However, the cadre-proposing mechanism produces a narrower range of t-statistics across the various assumptions for candidate preferences. Moreover, as seen in Figure 36, which side proposes in Deferred Acceptance also affects the performance in terms of average preference rank resulting from the matching. However, this distinction is larger for candidates than for cadres as candidates have more correlated preferences.

Although these stylized simulations are based on algorithmic assumptions over cadre preferences, they serve as a benchmark to suggest that introducing two-sided matching over dimensions like language, can also outperform one-sided mechanisms like the New Mechanism, in terms of bureaucratic quality balance. This is in addition to the the match quality improvement, in this case, brought about by matching more bureaucrats with local language proficiency.

6.4.1. *Implementation of Reservations via Soft Constraints.*
The two-sided simulations thus far have ignored all constraints. In the IAS setting, we never have unfilled vacancies by design because the market is balanced (i.e., UPSC sets exam rank cutoffs to ensure there are exactly as many candidates as there are vacancies) and because there are no matches which candidates or cadres can deem to be unacceptable (i.e., truncation of preferences is ruled out). Hence, we can ignore concerns such as regional balance constraints and Rural Hospital problem. Instead, we are faced with incorporating the reservations for quota candidates and insider candidates. Since candidates belonging

[48]These allocations possess the usual Deferred Acceptance properties: candidate-proposing is the candidate-optimal stable matching and is strategyproof for candidates, while cadre-proposing side is the cadre-optimal stable matching and strategyproof for cadres.

to SC, ST, and OBC categories can qualify under the General merit cutoff if their exam rank is high enough, each quota category has weakly more candidates than vacancies. In our data from 2005-2014, there are always strictly more OBC candidates than OBC vacancies, weakly more SC/ST than SC/ST vacancies, and hence strictly less General candidates than vacancies. However, because there is concentration and asymmetric representation in which states produce exam toppers, across all years, there are fewer insiders allotted compared to insider vacancies. This structure on the inputs—the initial rosters of vacancies and candidates— implies that implementation with hard constraints (reserved seats) will necessarily be wasteful.

Thus, we implement the reservation policies using Deferred Acceptance with soft constraints: some seats prioritized for insiders and/or quota candidates. Each cadre's preference is assumed to be lexicographic in language by popularity and exam rank and the cadre's preference is cloned to represent each vacancy in the cadre. Then, as per the count specified in roster of vacancies, certain seats are deemed priority seats for which the cadre preferences are updated to reflect the priority: all candidates who meet the reservation category are moved to the top of the list while maintaining the order of the cadre's preferences. This implements the soft constraint: the reserve for reservation seats is reflected in the priority seats, and the soft constraint is implied by these seats first giving priority to reservation candidates at the top of their artificial preferences, followed by their preferences over the remaining non-reservation candidates. This ensures a non-wasteful match.

First we introduce priorities only for insiders (Figures 37 and 38), then we allow priorities only for quotas SC/ST category and OBC category (Figures 39 and 40), and finally we allow quota x insider priorities (Figures 41 and 42). The candidate's preferences over cloned vacancies of cadres, which were arbitrarily ordered previously as it did not affect the allocation, can now be used to further promote reservation categories. By making all candidates apply first to the non-prioritized seats and then to the prioritized seats, we allow for the possibility that some prioritized candidates qualify for non-prioritized seats, leading to weakly less competition for the remaining prioritized candidates for their prioritized category's priority seats. For example, when imposing quota x insider constraints, all candidates prefer outsider seats to insider seats, and within each group, prefer General, OBC, and then SC/ST. The effect of this can be seen in Figures 40 and 42, where SC candidates tend to get more preferred cadres, OBC candidates perform slightly worse, and comparatively, General candidates perform the worst on average. This ordering of priorities is an important mechanism feature for the designer to target which groups to make relatively better off.

Of course, these matching allocations will be stable with regards to justified envy: no blocking pairs once candidates and cadres take into account the ordering of priorities set for the reservation seats by the mechanism designer.

Lastly, this section highlights how even after we introduce all the insider and quota priorities, bureaucratic quality balance is still improved relative from the two-sided matching relative to the New Mechanism.

6.4.2. *Impact of Correlation in Candidate's Preferences.*
We observe some patterns when we consider the average preference rank for the match from the perspective of the candidates and the cadres (Figures 36, 38, 40, and 42).[49] Firstly, the more correlated candidate's preferences are, the worse off they are, particularly when they

[49]It is important to realize that in all these graphs, we take averages across cadres, hence sometimes it may appear as though cadres are better off with candidates proposing, but this is only because of the averaging

propose, as increased competition amongst candidates for highly sought-after positions leads to a lot of rejections.[50] Secondly, relative to the candidates, cadres are less responsive to both which side proposes in Deferred Acceptance and how correlated candidates' preferences are because cadre preferences are relatively less correlated.[51] One source of correlation in cadre's preferences over candidates arises because many states, especially in the north, rank Hindi amongst the most commonly spoken languages. Thus candidates who speak Hindi as their mother tongue, tend to be higher up in many states' rank order preferences. We anticipate that if we consider preferences by expertise, preferences over candidates might be even less correlated across cadres. However, if states care just about exam ranks of the candidates, then cadre preferences are perfectly correlated with all states having the same ranking over candidates.

The correlation in preferences is also consequential for the uniformity in average preference rank for the match across cadres. In Figure 43, we see that when candidates have correlated preferences (block preferences in black and closeness preferences in red), the variance of average preference rank for the match across cadres is higher than when candidates' preferences are less correlated (Uncorrelated in blue and Res3 in green). Furthermore, when candidates' preferences are correlated, the variance tends to be lower with candidates proposing (dashed red and black lines). On the other hand, when candidates' preferences are relatively less correlated, the variance tends to be lower with cadres proposing (solid blue and green lines). Thus, from the standpoint of promoting uniformity in welfare across cadres, which side should propose in the Deferred Acceptance mechanism should depend on the relative correlation of the preferences of the two sides. Based on our simulation results, we conjecture that it is better for the more correlated side to propose and have the less correlated side break ties to prevent bunching and alleviate imbalance. Formalizing relative correlations across the sides of the market and why this probabilistically performs better than having the less correlated side propose and the more correlated side break ties is an interesting question to pursue in future research.

7. Preference vs. Performance Trade-off

This paper brings attention to a fundamental trade-off when it comes to designing allocation procedures for managed organizations. On the one hand, the designer wants to accommodate individuals' preferences to keep the members of the organization content, motivated, and prevent exists. However, this can come at a loss for the organization's performance and productivity as a whole. To illustrate this trade-off, we use the empirical estimates of i) average exam rank in state on revenue and ii) the discrete choice estimates of how candidates rank preferences, and compare revenue-optimal and preference-optimal allocations to highlight the fundamental tension between optimizing preferences and outcomes.[52]

over varying intensities of improvements. Deferred Acceptance produces the optimal stable matching for the proposing side; we graph aggregates for simplicity.

[50]See Celik (2014), Knuth (1997), and Caldarelli and Copocci (2001) for comments and simulations regarding Deferred Acceptance with correlated preferences.

[51]Such statements on welfare are made strictly from an ordinal (and not cardinal) utility standpoint.

[52]There are many possible social welfare weights a social planner can place on: quality balance, development, revenue, diversity, embeddedness, preferences of state/bureaucrats, SR vs. LR policies, ... As an illustrative exercise, we consider optimizing total revenue. Moreover, this optimization depends on the underlying revenue collection econometric model: is inefficiency/corruption happening i) on the margin, ii) as a percentage

We compute the worst and best[53] possible allocations for own tax revenue, and difference the counterfactual own tax revenues to give us the total gains. Figure 45 shows the fraction of the total gains realized by the actual mechanisms used in practice and the corresponding revenue loss relative to the revenue-optimal assignment. While the Old Mechanism captured about 75% of the gains, the New Mechanism only captures 55%.

The Preference vs. Performance Trade-off is illustrated in Figures 46 and 47. Figure 46 shows how revenue-optimal allocations allocate average preference rank of 13, whereas preference-optimal (minimizing average prefrence rank) allocates average preference rank of out of 5 out of 24 cadres. However, preference-optimal can only capture about 65% of the total gains in own tax revenues (Figure 47).

It is the correlation across individuals' preferences and how much preference-based sorting the mechanism admits, that determines how much of the gains in revenue will be lost when incorporating preferences of individuals. As shown in Figure 48, the Old Mechanism (black) which does not incorporate any preferences other than home state preference, captures about 90% of the total gains in own tax revenues. If preferences were uncorrelated (red), a serial dictatorship in order of exam rank takes preferences in to account and minimally affects the percentage gains captured in own tax revenues. However, if preferences of individuals are driven by distance from home (purple) or if good cadres are ranked randomly within block above the block of bad cadres also ranked randomly within block (green), then incorporating preferences via serial dictatorship in order of exam rank comes at a sizable loss in own tax revenues.

8. Extensions to Other Civil Services & Other Matching Applications

This analysis can be immediately extended to the two other All-India Services—Indian Police Service (IPS) and Indian Forest Service (IFoS)— which share the same mechanisms we analyzed above. Despite more limited data availability, we show in Appendix A that analogous imbalances on the quality dimension with the New Mechanism arise in the IPS and IFoS (see Figure 49). Moreover, for years 2008 for IPS and 2015 for IFoS, for which we have preference rank order data, we highlight the correlation in preferences where bad cadres are consistently ranked very low by most civil servants (Tables 17 and 19) and the near unanimous preference for being an insider (Table 18).

Applying matching theory to study and design allocation of civil servants and bureaucrats is more general than just the Indian problem analyzed in this paper. Mandarin bureaucracies, where competitive examinations are used to rank and select top performers, are prevalent globally in countries including the US, China, Brazil, and France. Concerns of quality balance, affirmative action, and regional representation are also universal in bureaucracies around the world. The various systems of recruiting and allocating civil servants used around the world can be classified into four categories: 1) application to a particular service or post (e.g., Chinese bureaucracy), 2) appointment to a particular service or post (e.g., US President appoints and Congress approves senior civil servant appointments), 3) centralized, synchronous assignment of many bureaucrats to posts (e.g., the cadre allocation of IAS officers), and 4) centralized, dynamic assignment of civil servants (e.g., US Foreign

of total revenues, or iii) on a per capita basis. We use the estimates from Section 5.1 which assumes that lowering the average exam rank has the same dollar effect on the margin in every state.

[53]The revenue-optimal matching assigns the best scorers to the states with fewest officers to maximize weighted impact.

Service where transfers and promotions are made dynamically as openings arise). The first two categories are more aligned with decentralized labor market models involving search. Static matching theory plays a key role in centralized, synchronous assignment as we see in this paper. Whereas, dynamic matching theory can be used to study the fourth category of civil service allocation systems: a promising avenue for future research.

Lastly, the novel constraint for global quality balance that we identify in this paper, is also applicable to other settings such as assigning teachers to schools, cadets to branches/battalions in the army, and workers to various teams/divisions in a firm.[54] For example, the government may want to make different schools and school districts roughly comparable in teacher quality and the military may seek uniformity of talent across various divisions. Understanding such constraints and designing mechanisms to address the underlying correlations in the data is also a promising area for future work.

9. Conclusion

The design of civil service allocation mechanisms matters. Certain imbalances, like the underlying correlations in officers cadre preferences, can feed through procedural designs and translate to imbalances in development outcomes and bureaucratic performance. If such imbalances are not addressed, vicious cycles can emerge: relatively higher quality civil servants avoid disadvantaged cadres, outcomes in these distressed areas further deteriorate, and the preference to avoid these regions is further reinforced. It cannot be overstated how important it is for a country to effectively allocate its talent, particularly in allocating elite civil servants who are the pivotal state actors implementing government policies, distributing public services, and enforcing state capacity. Thus, using tools of matching theory to analyze and improve the design of such assignment procedures to better suit the governments needs seems like a productive enterprise.

In this paper, we study the impact of various matching mechanisms for the assignment of top-level Indian civil servants to state cadres. As the central planner and a mechanism designer with a social welfare function, the government often wants to impose constraints, such as uniformity of bureaucratic quality across state cadres. These considerations do not necessarily arise in canonical, more market-driven matching applications, like school choice. Such constraints underscore the importance of mechanisms addressing the underlying correlations in preferences and hidden correlations amongst covariates (such as exam rank, state of origin, quota, education, age, and language proficiency), which are generally taken as given and unaddressed in most matching applications. However, systematic imbalances, such as those resulting from the New Mechanism, can be detrimental to outcomes; in this instance, developmental outcomes and bureaucratic performance. Particularly, we highlight how the change in mechanism has adversely affected uniformity of state capacity by causing imbalances in tax revenue collection and Human Development Index across states. To illustrate how certain mechanism characteristics address (or fail to address) such imbalances and correlations, we derive an approximate ranking of mechanisms and analyze policy interventions,

[54]Terrier (2014) and Combe et al. (2018) study teacher allocation in France. Sonmez (2013) and Sonmez and Switzer (2013) study the matching of ROTC and cadets to various divisions of the military. The Indian Army has explicit constraints in the Indian Army Choice of Arms Procedure, to ensure an equitable caliber spread (referring to merit rank), along with other balance constraints of age profile, type of entry, and regional distribution across the various arms and services. Cowgill and Koning (2018) have a Harvard Business School case on matching mechanisms used by Google for internal team assignments

such as grouping cadres and nudging candidate preferences. Moreover, we suggest that an increasing need for domain-specific knowledge and local language proficiency given that over 50 languages are spoken in India, might necessitate two-sided matching mechanisms where cadres' preferences over candidates are also incorporated. In this paper, we have highlighted the trade-offs associated with various mechanism features and policies in addressing the imbalances and correlations in the data; but ultimately, it is up to the Indian government to decide how to resolve these trade-offs and optimize given their desired weights on the constraints and outcomes.

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Results shown in most Tables and Figures show analysis based on data sets primarily from the following sources (otherwise, see figure/table caption for source):

- **2005-2015 assignments, vacancies, candidates, and exam ranks from Ministry of Personnel, Public Grievances, and Pensions (http://persmin.gov.in/AIS1/QryCA.asp.)**
- **Civil Lists 2001-2016 and 2017 Civil List (http://civillist.ias.nic.in/IndexCL.htm)**
- **Executive sheets for IAS batches 1984 to 2007 from Ferguson and Hasan (2013) which include language, training, posting history for each IAS officer**
- **Executive sheets for IAS batches 2005-2016 from Department of Personnel and Training and Ministry of Personnel, Public Grievances, and Pensions which include language, training, posting history for each IAS officer (https://supremo.nic.in/knowyourofficerIAs.aspx)**

Table 2. Effect of New Mechanism on Average Exam Rank and Normalized State Average Exam Rank (2005-2013).

	(1) Avg. St. Exam Rank	(2) Normalized St. Exam Rank
Bad cadre × New Mechanism	114.8***	0.784***
	(23.14)	(0.190)
Constant	78.60***	-0.115
	(9.207)	(0.0895)
Year FE	✓	✓
State FE	✓	✓
Observations	216	216

Notes: This table shows estimates of regression $Y_{st} = \alpha + \beta \mathbb{1}_{BadCadre} * \mathbb{1}_{NewMechYears} + \eta_s + \tau_t + \epsilon_{it}$ for Average Exam Rank and Normalized State Average Exam Rank. Normalized State Exam Rank is $\frac{\mu_c - \mu}{\sigma}$ where μ_s is state cadre c's average exam rank of assigned candidates, μ =mean(μ_c) is the average exam rank across states and σ=stddev(μ_c). We see that from 2008 onwards, with the New Mechanism, the good and bad cadres diverged in quality of assigned candidates. See Table 23 for year-by-year effects and placebo tests.

Standard errors in parentheses are clustered at the state cadre level

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3. Driving factors for Old vs. New Mechanism performance.

	(1) AvgExmRnk	(2) AvgExmRnk	(3) AvgExmRnk	(4) AvgExmRnk
Number of Toppers	-2.785			
	(1.858)			
Avg Exm Rnk From Cadre		0.268***		
		(0.0932)		
Cadre No In Cycle OldMech			1.473*	
			(0.729)	
Order of Group OldMech				8.840*
				(4.375)
Constant	88.58***	49.34***	60.18***	57.97***
	(11.16)	(16.60)	(9.977)	(10.86)
Year FE	✓	✓	✓	✓
State FE	✓	✓	✓	✓
Observations	216	186	72	72

Notes: The average exam rank of assigned to a state cadre depends on the a) number of exam toppers this cadre produces (*Column (1)*), b) the average exam rank of the exam toppers this cadre produces (*Column (2)*), c) the rank in the 1-24 cycle in the Old Mechanism (*Column (3)*), and d) the order of the group which contains the cadre in the 1-24 cycle in the Old Mechanism (*Column (4)*). Because of the insider priority, the higher the number of exam toppers from the cadre and the better their average exam rank, the better average exam rank is in the cadre. In the Old Mechanism, the group permutations producing the 1-24 cycle also affect average exam rank in the cadre with lower groups in the pecking order getting candidates worse average exam ranks.
Standard errors in parentheses are clustered at the state cadre level
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4. Discrete Choice Analysis of Cadre Preferences.

	(1) Cond logit	(2) Cond logit	(3) Rnk-ordered logit	(4) Rnk-ordered logit	(5) Lin reg
	Top5	Bottom5	PrefRank	PrefRank	PrefRank
DistancefromHome (*thou.*)	-4.09***	1.94***	-1.31***	-0.673**	-6.49***
	(0.354)	(0.246)	(0.125)	(0.270)	(0.313)
GSDPpercapita04-05 (*mil.*)	32.0***	-5.26	10.8***	10.7***	53.3***
	(12.2)	(7.05)	(3.70)	(3.67)	(19.4)
HealthIndex08	1.316	-2.331***	1.359***	1.543***	7.188***
	(0.922)	(0.813)	(0.339)	(0.355)	(1.841)
%ageRurRoadsSurfaced	1.771***	-3.128***	1.555***	1.537***	9.425***
	(0.376)	(0.253)	(0.105)	(0.106)	(0.598)
DistancefromHome^2 (*mil.*)				-0.447**	
				(0.179)	
Constant					4.897***
					(0.961)
Observations	2783	2622	2806	2806	2806
R^2					0.277
LL	-799.50	-982.087	-6020.5567	-6018.765	
LL (intercept only)	-1105.08	-1182.97			

Notes: *Columns (1)*, *(2)* report conditional logits where the dependent variable is indicator variable for cadre being ranked amongst the top 5, bottom 5 ranks respectively. *Columns (3)* and *(4)* report rank-ordered logits (or exploded logits) for the cadre preferences. *Column (5)* uses linear regression specification similar to rank-ordered logit from column (3). Data: i) Distance from Home State is the distance in miles between capital cities of the home cadre and ranked cadre. ii) GSDP Per Capita 04-5 is the gross state domestic product per capita from year 2004-2005. iii) Health Index 08 is the health index for 2008 computed in forming the Human Development Index from the India Human Development Report 2011. iv) %age Rural Roads Surfaced is the percentage of rural roads which are surfaced from data.gov.in. See Table 30 for the summary statistics of these variables.
Standard errors in parentheses are clustered at an individual level
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5. Relative Effect Sizes in Cadre Preference Discrete Choice Model in terms of 1 standard deviation of Distance from Home State.

	(1) Cond logit PrefRank Top5	(2) Cond logit PrefRank Bottom5	(3) Rk-ordered logit PrefRank
DistancefromHome	1	1	1
GSDPpercapita04-05	5.00	14.43	4.74
HealthIndex08	11.84	3.17	3.67
%ageRurRoadsSurfaced	4.05	1.09	1.48

Notes: This table calculates the 1 standard deviation effect of i) distance from home state in miles, ii) GSDP per capita 04-05, iii) health index 2008, and iv) percentage of rural roads surfaced, as a factor of 1 standard deviation effect of distance from home state in miles.

Table 6. Relative Effect Sizes in Cadre Preference Discrete Choice Model in terms of Distance from Home State in Miles.

	(1) Conditional logit PrefRank Top5	(2) Conditional logit PrefRank Bottom5	(3) Rnk-ordered logit PrefRank
DistancefromHome	381	381	381
GSDPpercapita04-05	76	26	80
HealthIndex08	32	120	103
%ageRurRoadsSurfaced	94	350	257

Notes: This table calculates the 1 standard deviation effect of i) Distance from Home State in miles, ii) GSDP per capita 04-05, iii) health index 2008, and iv) percentage of rural roads surfaced, in terms of distance from home state in miles.

Table 7. Distance Willing to Travel for Each Cadre Relative to Average Cadre.

Cadre	Distance (miles)
Punjab	568
Gujarat	520
Haryana	506
AGMUT	437
Himachal Pradesh	319
Maharashtra	298
Uttar Pradesh	222
Madhya Pradesh	192
Sikkim	191
Orissa	161
Chhattisgarh	157
Tamil Nadu	48
Rajasthan	-6
Kerala	-42
Andhra Pradesh	-81
Uttarakhand	-101
Jammu & Kashmir	-105
Jharkhand	-126
Karnataka	-140
Bihar	-360
Nagaland	-540
Manipur-Tripura	-584
West Bengal	-658
Assam-Meghalaya	-837

Notes: Positive (negative) values give the distance in miles that candidates are willing to travel to get (avoid) the cadre relative to the average cadre. Notice that many of the bad cadres appear at the very bottom of the list.

Table 8. A Cadre's Production of Exam Toppers.

	(1) Poisson Reg NumberToppers	(2) Poisson Reg NumberToppers	(3) Poisson Reg NumberToppers
HealthIndex08	5.943***	4.773***	3.733***
	(0.823)	(0.848)	(0.905)
PerCapitaIncome2011-12 (*mil.*)	9.77***	6.97***	5.76***
	(2.44)	(2.29)	(2.22)
Population_Census2011 (*bil.*)	15.2***	17.6***	13.8***
	(0.680)	(1.08)	(0.703)
LiteracyRate2011Census	-0.0875***		
	(0.0125)		
LiteracyRateRural2011		-0.0363**	
		(0.0163)	
LiteracyRateUrban2011		-0.0437**	
		(0.0202)	
EducationIndex2008			-2.298**
			(0.922)
Constant	2.610***	3.025***	-0.881**
	(0.906)	(1.096)	(0.436)
Year Fixed Effects	✓	✓	✓
Observations	216	216	216

Notes: Poisson regressions to deal with data of counts of exam toppers from each cadre from 2005-2013. Data: 1) Health Index 2008 and 2) Education Index 2008 from India Human Development Report 2011, 3) Per capita income 2011-12, 4) Population 2011 and 5) Literacy rate, 6) Literacy rate for rural areas and 7) Literacy rate for urban areas from 2011 Census.
Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 9. Structural Break: Effect of Mechanism change on Revenue.

	(1) Own Tax	(2) Non-Tax
Bad cadre × New Mech. × lineartrend	-1336.6**	-111.0
	(604.5)	(94.80)
Bad cadre × New Mech.	5361.9	-352.6
	(3897.7)	(335.8)
lineartrend	6779.3***	594.5***
	(18.79)	(22.33)
Constant	5035.9***	812.4***
	(330.2)	(110.4)
Year FE	✓	✓
State FE	✓	✓
State Linear Time Trend	✓	✓
Observations	280	280

Notes: We use state-level revenue data from 12th and 13th Finance Commission Reports covering fiscal years 2005 to 2015 to estimate $Y_{st} = \alpha + \eta_s + \gamma_s * t + \beta \mathbb{1}_{BadCadre} * \mathbb{1}_{NewMechYears} * t + \tau_t + \epsilon_{st}$. Hence, β captures the difference in change in linear trends across good and bad cadres due to the New Mechanism. The effect on non-tax revenues (*Column (2)*) is not significant, in line with this being a placebo test for revenue categories outside the jurisdiction of IAS officers. See Figure 20 difference-in-difference graphs, and for robustness on non-tax revenue regressions see Figure 21 and Table 24.
Standard errors in parentheses are clustered at the state cadre level
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 10. Effect of Exam Rank & Normalized Exam Rank on Own Tax Revenue.

	(1) OLS	(2) IV_DiD	(3) OLS	(4) IV_DiD
	Own Tax	Own Tax	Own Tax	Own Tax
Avg Exam Rank	-20.11***	-85.11***		
	(6.69)	(23.71)		
Normalized Exam Rank			-2492.8***	-11909.6***
			(767.1)	(3338.6)
Constant	11567.7***	69129.0***	9704.0***	54332.8***
	(1389.5)	(4917.0)	(1687.0)	(1798.8)
Year FE	✓	✓	✓	✓
State FE	✓	✓	✓	✓
Observations	224	224	224	224

Notes: We use state-level revenue data from 12th and 13th Finance Commission Reports for fiscal years 2008-2015 (IAS batches 2005-2012) to estimate OLS $Y_{st} = \alpha + \beta X + \eta_s + \tau_t + \epsilon_{st}$ for Average Exam Rank and Normalized State Average Exam Rank. IV estimates instrument for X using first stage $\hat{X}_{st} = \alpha + \beta \mathbb{1}_{BadCadre} * \mathbb{1}_{NewMechYears} * t + \eta_s + \tau_t + \mu st$.
Standard errors in parentheses are clustered at the state cadre level
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 11. De-trended Own-tax and Non-tax Revenue Difference-in-Difference.

	(1)	(2)	(3)	(4)	(5)	(6)
	DetOwnTax	DetOwnTax	DetOwnTax	DetNonTax	DetNonTax	DetNonTax
Bad cadre × New Mech.	-5330.9***			-1240.4		
	(1548.8)			(753.6)		
bad15		-8365.9***	-8194.1***		-1509.4	-1481.6
		(2639.4)	(2601.0)		(933.3)	(942.0)
bad14		-6472.8***	-6301.0***		-1279.4	-1251.7
		(1937.9)	(1904.5)		(843.3)	(851.2)
bad13		-4984.9***	-4813.1***		-1234.3	-1206.5
		(1472.3)	(1452.3)		(754.5)	(761.9)
bad12		-3822.9***	-3651.1***		-1169.0*	-1141.3
		(1217.0)	(1217.3)		(676.8)	(683.4)
bad11		-3007.9**	-2836.1**		-1009.7	-981.9
		(1110.5)	(1129.1)		(607.6)	(613.0)
bad10			-9.654*			-1.304
			(4.746)			(1.521)
bad09			271.4**			43.09**
			(120.0)			(16.74)
bad08			345.3**			56.57**
			(154.2)			(20.54)
bad07			252.1**			40.48***
			(110.5)			(14.37)
Constant	7540.7***	7540.7***	7540.7***	1205.1***	1205.1***	1205.1***
	(476.4)	(479.9)	(483.3)	(245.0)	(246.9)	(248.7)
Year FE	✓	✓	✓	✓	✓	✓
State FE	✓	✓	✓	✓	✓	✓
Observations	280	280	280	280	280	280

Notes: We use state-level revenue data from 12th and 13th Finance Commission Reports for fiscal years 2008 to 2015 (IAS batches 2005-2012). We de-trend each state using its own Old Mechanism (2005-2010) trend, and then estimate difference-in-difference on the de-trended data: $Y_{st} = \alpha + \beta \mathbb{1}_{BadCadre} * \mathbb{1}_{NewMechYears} + \eta_s + \tau_t + \epsilon_{st}$, in *Columns (1)* and *(4)*. *Columns (2)* and *(5)* breakdown the New Mechanism effects into year-by-year effects for 2011-2015. *Columns (3)* and *(6)* add placebo treatment effects for years 2007-2010. We see that the placebo, although significant, are at least an order of magnitude smaller than the New Mechanism effects. The effect on non-tax revenues (*Columns (4) -(6)*) for New Mechanism years (2011-15) are all not significant, in line with this being a placebo test for revenue categories outside the jurisdiction of IAS officers. See Figure 24 for graph of placebo tests. See Figure 22 for difference-in-difference graphs, and for robustness on non-tax revenue regressions see Figure 23 and Table 24.

Standard errors in parentheses are clustered at the state cadre level

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 12. Forgone Own Tax Revenue due to Quota Affirmative Action Policies (Counterfactual).

Res	AvgExmRnk w/out Res	AvgExmRnk w/ Res	OwnTax Rs.(cr.)	OwnTax $(mil.)
All	90.5	199.2	9250	$1,423
ST	172.3	199.2	2289.9	$352
SC	138.9	199.2	5128.3	$789
OBC	177.0	199.2	1891.3	$291

Notes: This table shows the average exam rank across all candidates with reservation and without reservation for year 2015. The counterfactual of without reservation category Res replaces the Res category candidates with the highest non-qualifying candidates by exam rank. Exchange rate is assumed at 65 $\frac{INR}{USD}$. Four counterfactuals are shown: without any reservation, without ST, without SC, and without OBC. See Tables 26, 27, 28, and 29 for simulations for all years for each affirmative action category.

Table 13. Difference-in-difference effect of New Mechanism on Human Development Index (HDI).

	(1) HDI
Bad cadre × New Mechanism	-.0488**
	(.0224)
Constant	.2598***
	(.0143)
Year FE	✓
State FE	✓
Observations	196

Notes: Data used is HDI for years 1983, 1988, 1993, 2000, 2005, 2010, and 2012 constructed by Mukherjee et al. (2014).
Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 14. Effect of New Mechanism on Age of Candidates.

	(1) Age	(2) Age
Bad cadre × New Mechanism	0.466*	0.396
	(0.273)	(0.269)
Constant	24.45***	24.45***
	(0.348)	(0.360)
Year FE	✓	✓
State FE	✓	✓
Observations	662	684
Number of cadres	23	24

Notes: Regressing $AverageAge_{st} = \alpha + \beta_1 \mathbb{1}_{BadCadre} * \mathbb{1}_{NewMechYears} + \eta_s + \tau_t + \epsilon_{st}$. Since $\beta_1 > 0$, bad cadres get older candidates under the New Mechanism. The first column drops Sikkim which has 1 IAS officer allotted per year and hence causes a lot of variance. Particularly, Sikkim is allotted a 25 year-old candidate in 2011, which makes it the lowest average age across all states for that year. The second column includes Sikkim. Data is from civil lists 1984-2013 (Years 1984 to 2007 from Ferguson and Hasan (2013)).
Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 15. Ratio of Exam Toppers relative to Vacancies for new states formed in 2000.

	Candidates	Vacancies	Ratio
Jharkhand	42	59	0.71
Uttarakhand	17	33	0.52
Chhattisgarh	14	63	0.22

Notes: The low ratio of exam toppers relative to posted vacancies in Chhattisgarh compared to Jharkhand and Uttarakhand might help explain why Chhattisgarh does poorly in average exam ranks amongst the new states.

Table 16. Comparing performance of various mechanisms in achieving regional mobility.

2017 Mechanism w/ Naive Truthtelling

Regional Exm Rank		**Reg Mobility from Zones**				**Reg Mobility to Zones**			
	AvgExmRnk		Out	In	%Out		Out	In	%Out
Zone1	231	Zone1	10	14	.42	Zone1	19	14	.56
Zone2	186	Zone2	8	17	.32	Zone2	13	17	.43
Zone3	168	Zone3	9	8	.53	Zone3	8	8	.5
Zone4	398	Zone4	23	4	.85	Zone1	1	4	.2
Zone5	320	Zone5	11	18	.38	Zone20	20	18	.53
Variance Exm Rank									
Variance	9416								

DA w/ regional & insider-outsider constraints

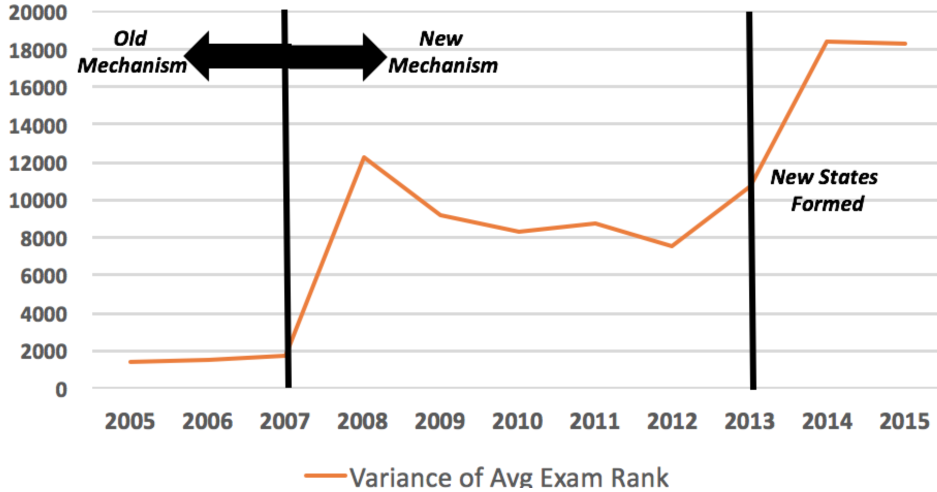
Regional Exm Rank		**Reg Mobility from Zones**				**Reg Mobility to Zones**			
	AvgExmRnk		Out	In	%Out		Out	In	%Out
Zone1	237	Zone1	15	9	.62	Zone1	24	9	.73
Zone2	282	Zone2	19	6	.76	Zone2	24	6	.80
Zone3	241	Zone3	13	4	.76	Zone3	12	4	.75
Zone4	355	Zone4	25	2	.93	Zone4	3	2	.6
Zone5	230	Zone5	21	8	.72	Zone5	30	8	.79
Variance Exm Rank									
Variance	2727								

2008 New Mechanism

Regional Exm Rank		**Reg Mobility from Zones**				**Reg Mobility to Zones**			
	AvgExmRnk		Out	In	%Out		Out	In	%Out
Zone1	193	Zone1	3	21	.12	Zone1	12	21	.36
Zone2	196	Zone2	2	23	.08	Zone2	7	23	.23
Zone3	197	Zone3	5	12	.29	Zone3	4	12	.25
Zone4	468	Zone4	22	5	.81	Zone4	0	5	0
Zone5	261	Zone5	1	28	.03	Zone5	10	28	.26
Variance Exm Rank									
Variance	13937								

Notes: Simulations comparing the performance of various mechanisms in achieving regional mobility and furthering the national integration and unity purpose of the All-India Services. Using 2008 IPS Preferences and vacancies, we compare three mechanisms: i) DA with regional constraints, ii) 2017 Mechanism, and iii) 2008 New Mechanism.

Figure 4. Variance of within-cadre average exam rank across all cadres.



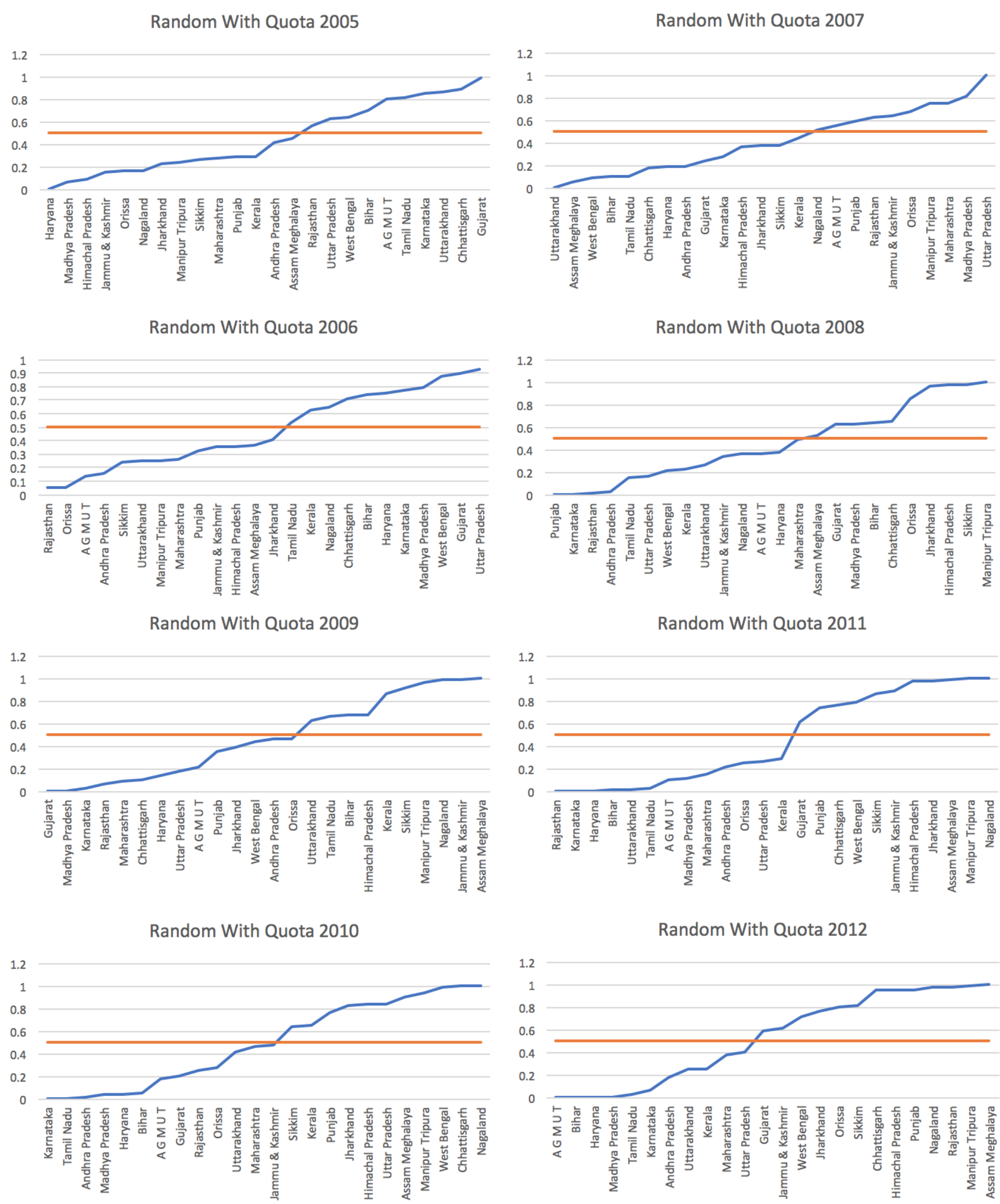
Notes: Plotting the variance of within-cadre average exam rank across all cadres shows the increases in variance with the New Mechanism (2008 onwards) and with the formation of new states in 2014.

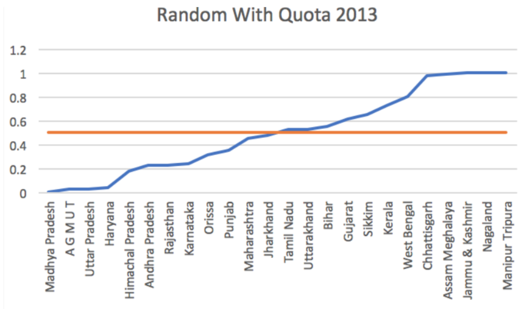
Figure 5. Comparing Average Exam Rank for Selected Cadres with Random Allocations.

Notes: For a selected subset of cadres (Haryana, Andhra Pradesh, Maharashtra, Manipur-Tripura, Nagaland, and Assam Meghalaya), this figure shows the percentage of time a cadre's actual average exam rank is higher than the average exam rank produced by Random within Quotas mechanism simulations. We see that with the New Mechanism (2008-2013), two groups of cadres emerge: those that systematically under-perform (*dashed*) and those that systematically do better (*solid*) relative to random within quota. Figure 6 shows all cadres for each year, while this plots the time-series for a subset the cadres to highlight the two groups that emerge with the New Mechanism. Note that with the Old Mechanism (2005-2007), performance for any given cadre also exhibits changes across years. This temporal balancing occurs due to the 1:24 cycles and group rotations present in the Old Mechanism.

Figure 6. Comparing Average Exam Rank for each Cadre with Random Allocations.

Notes: Percentage of time a state's actual average exam rank is higher than the average exam rank produced by Random within Quotas mechanism simulations. Relative to random assignments, 0.5 is a state performing like random, > 0.5 is a state under-performing relative to random, while < 0.5 is a state over-performing relative to random. The losers and winners tend to alternate in the Old Mechanism year by year (2005-2007), whereas, starting from 2008, the bad cadres consistently under-perform relative to random within quota.





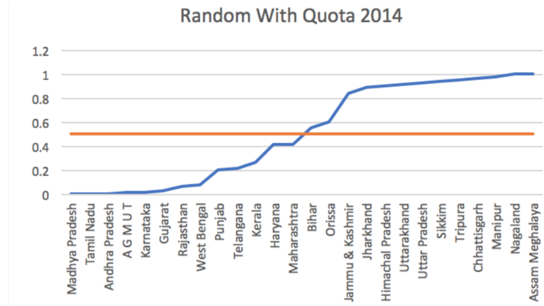
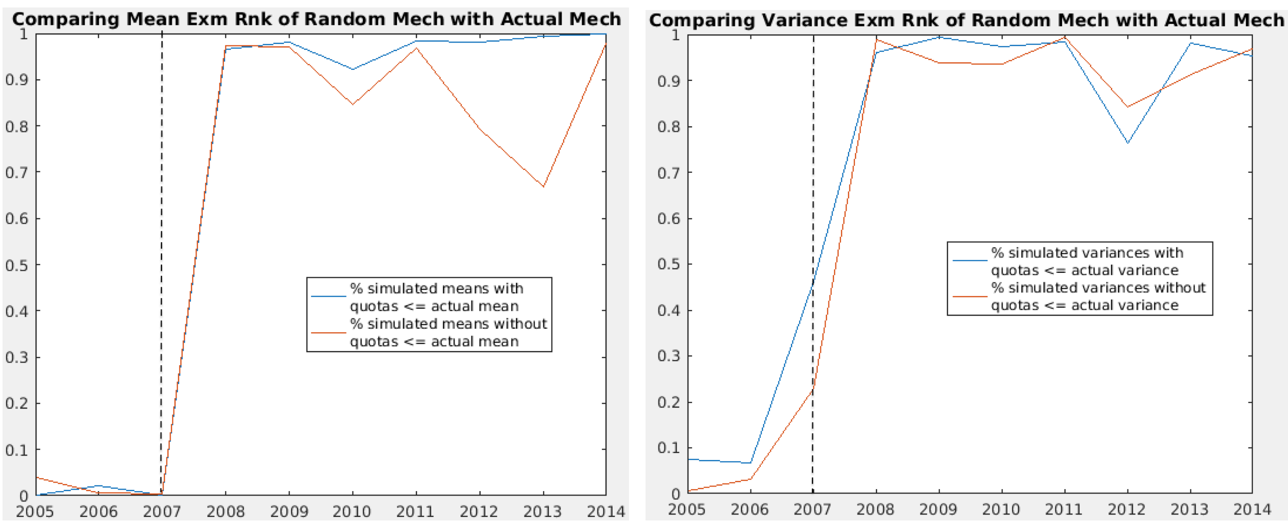
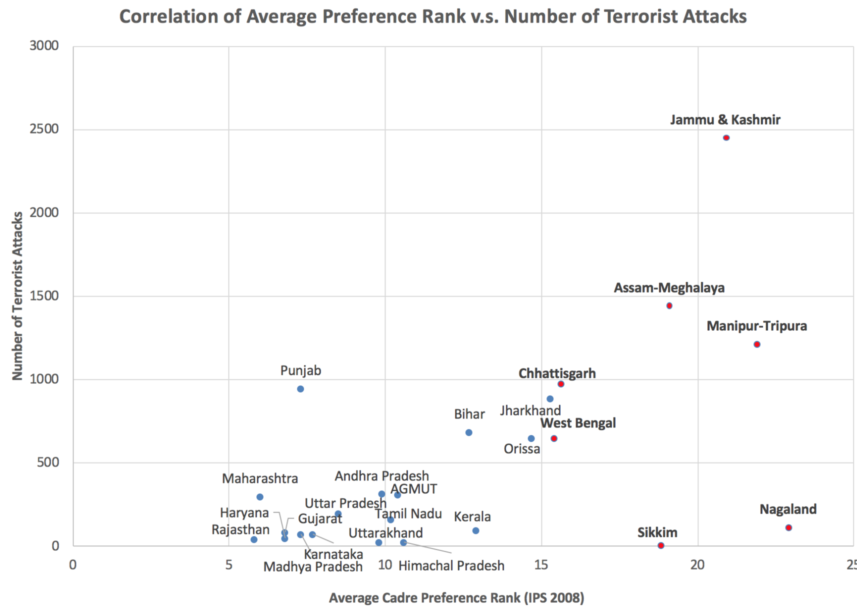


Figure 7. Comparing Performance of Old and New Mechanisms vs. Random Mechanism.



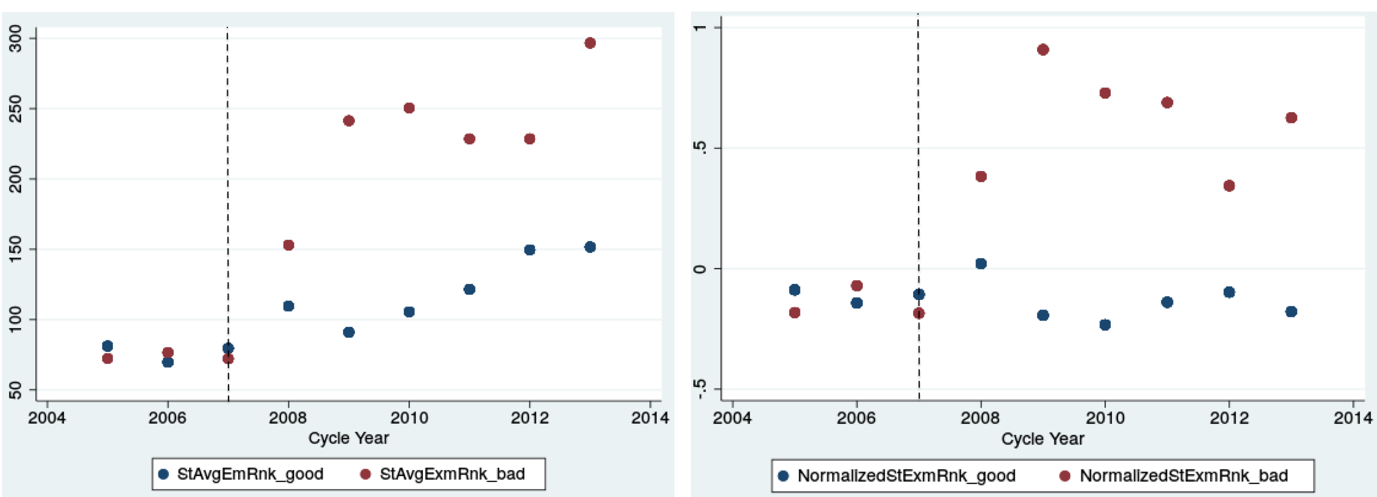
Notes: Percentage of means (*Left*) and variances (*Right*) of average exam ranks across cadres which are lower under random (orange) and random with quotas (blue) mechanisms than with actual assignments. Notice Old Mechanism years (2005-07) outperform random whereas New Mechanism years (2008 onwards) underperform relative to random.

Figure 8. Correlation between cadre's average preference rank and the number of terrorist attacks.



Notes: The plot shows the correlation between the cadre's average preference rank by the candidates (IPS 2008 batch, see Table 17) and the number of terrorist attacks (1970-2015). Bad cadres are marked by red dots and bold labels. Terrorist attack data from Global Terrorism Database *https://www.start.umd.edu/gtd/*

Figure 9. Effect of New Mechanism on Average Exam Rank across Good and Bad Cadres.



Notes: Average of within-cadre average exam rank (*left*) and Average of normalized state average exam rank (*right*), for Good (blue) and Bad (red) Cadres from 2005 to 2013. Normalized State Average Rank is $\frac{\mu_c - \mu}{\sigma}$ where μ_s is state cadre c's average exam rank of assigned candidates, μ =mean(μ_c) is the average exam rank across states, and σ=stddev(μ_c). We see that from 2008 onwards, with the New Mechanism, the good and bad cadres diverged in quality of assigned candidates.

Figure 10. Average exam rank differences between assigned insiders and outsiders by category.

	2005-2007 Exam Rank	2008-2013 Exam Rank	2014-2015 Exam Rank
General			
Insider	29.6	29.2	53.7
Outsider	52.4	77.4	84.2
O.B.C			
Insider	54.1	104.1	193.0
Outsider	86.5	155.5	286.8
S.C.			
Insider	130.3	244.5	323.3
Outsider	172.9	276.0	423.6
S.T.			
Insider	194.1	330.7	433.3
Outsider	208.1	409.8	497.7
OVERALL			
Insider	66.6	124.8	180.2
Outsider	95.3	156.0	226.7

Notes: Analysis separated into years 2005-07 (Old Mechanism), 2008-13 (New Mechanism), and 2014-15 (New Mechanism with new states).

Figure 11. Ratio of exam toppers to total vacancies from each state.

2005-2007		2008-2013		2014-2015	
State	**Ratio**	**State**	**Ratio**	**State**	**Ratio**
Tamil Nadu	2.67	Rajasthan	2.80	Haryana	4.17
Rajasthan	2.40	Haryana	2.39	Rajasthan	2.60
Andhra Pradesh	1.86	Tamil Nadu	1.92	A G M U T	2.05
Uttar Pradesh	1.80	Kerala	1.68	Maharashtra	1.73
Bihar	1.65	Uttar Pradesh	1.66	Tamil Nadu	1.50
Maharashtra	1.59	Bihar	1.65	Uttar Pradesh	1.41
A G M U T	1.44	Andhra Pradesh	1.45	Andhra Pradesh	1.33
Jharkhand	1.33	Maharashtra	1.36	Punjab	1.33
Punjab	1.18	Punjab	1.34	Telangana	1.18
Haryana	1.11	A G M U T	0.82	Karnataka	0.95
Karnataka	0.91	Karnataka	0.80	Jharkhand	0.93
Kerala	0.89	Jammu & Kashmir	0.73	Uttarakhand	0.86
Orissa	0.75	Jharkhand	0.55	Kerala	0.85
Uttarakhand	0.75	Himachal Pradesh	0.42	Jammu & Kashmir	0.83
Madhya Pradesh	0.53	Orissa	0.35	Bihar	0.68
West Bengal	0.47	Uttarakhand	0.33	Madhya Pradesh	0.54
Jammu & Kashmir	0.33	Chhattisgarh	0.31	Sikkim	0.50
Manipur Tripura	0.27	Manipur Tripura	0.30	Orissa	0.45
Himachal Pradesh	0.25	Sikkim	0.29	Himachal Pradesh	0.44
Gujarat	0.18	Madhya Pradesh	0.25	Manipur	0.43
Nagaland	0.13	Assam Meghalaya	0.24	West Bengal	0.24
Chhattisgarh	0.11	West Bengal	0.19	Gujarat	0.21
Assam Meghalaya	0.07	Gujarat	0.18	Chhattisgarh	0.11
Sikkim	0.00	Nagaland	0.00	Assam Meghalaya	0.07
				Nagaland	0.00
				Tripura	0.00

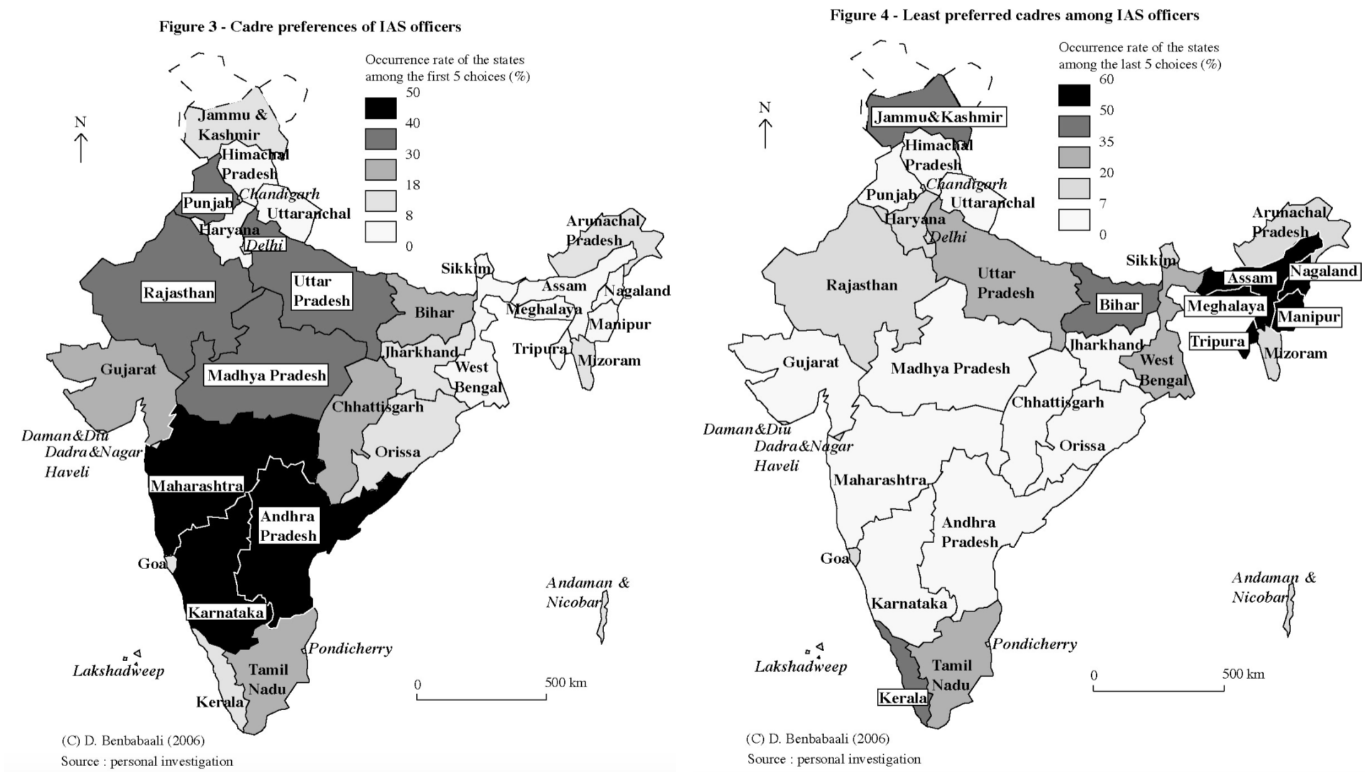
Notes: Analysis separated into years 2005-07 (Old Mechanism), 2008-13 (New Mechanism), and 2014-15 (New Mechanism with new states).

Figure 12. Average exam rank of candidates by Home State.

2005-2007 State	Rank	2008-2013 State	Rank	2014-2015 State	Rank
Chhattisgarh	23.0	Uttarakhand	54.5	Assam Meghalaya	16.0
Haryana	31.6	Haryana	79.8	Sikkim	63.0
West Bengal	39.4	Orissa	93.9	Madhya Pradesh	65.3
Kerala	40.8	Kerala	94.7	West Bengal	90.1
Orissa	41.7	Chhattisgarh	99.2	A G M U T	112.3
Jammu & Kashmir	47.5	A G M U T	104.4	Orissa	115.9
Uttar Pradesh	59.4	Madhya Pradesh	108.4	Bihar	139.0
Bihar	60.1	Bihar	119.8	Haryana	141.5
Jharkhand	64.7	West Bengal	123.5	Jharkhand	157.0
Gujarat	67.5	Uttar Pradesh	124.5	Gujarat	175.0
Himachal Pradesh	72.0	Tamil Nadu	131.9	Punjab	177.3
Punjab	77.4	Punjab	143.1	Kerala	195.5
Madhya Pradesh	86.6	Andhra Pradesh	155.7	Andhra Pradesh	206.7
Maharashtra	89.2	Jammu & Kashmir	156.3	Uttar Pradesh	227.4
A G M U T	89.6	Karnataka	165.5	Tamil Nadu	232.7
Uttarakhand	104.8	Maharashtra	167.7	Karnataka	246.2
Rajasthan	106.2	Assam Meghalaya	199.5	Rajasthan	271.9
Tamil Nadu	107.0	Jharkhand	207.5	Chhattisgarh	279.0
Andhra Pradesh	129.9	Manipur Tripura	219.2	Manipur	297.8
Karnataka	170.3	Rajasthan	238.0	Jammu & Kashmir	302.4
Assam Meghalaya	177.0	Gujarat	241.9	Telangana	320.3
Manipur Tripura	190.8	Himachal Pradesh	302.6	Himachal Pradesh	328.8
Nagaland	244.0	Sikkim	468.5	Maharashtra	341.2
Sikkim		Nagaland		Uttarakhand	564.5
				Nagaland	
				Tripura	

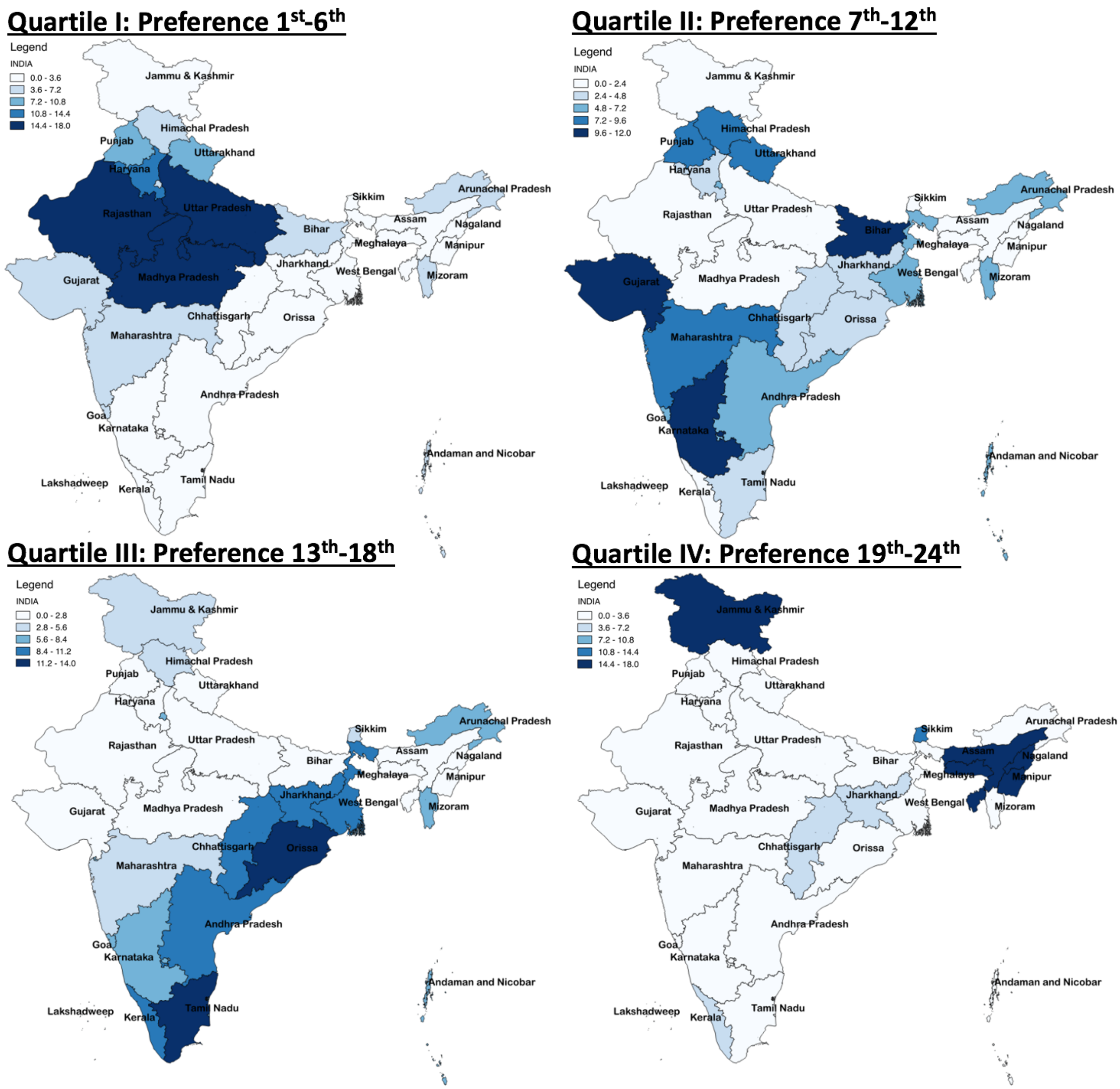
Notes: Analysis separated into years 2005-07 (Old Mechanism), 2008-13 (New Mechanism), and 2014-15 (New Mechanism with new states).

Figure 13. Most versus Least Preferred Cadres: IAS Cadre Preferences.



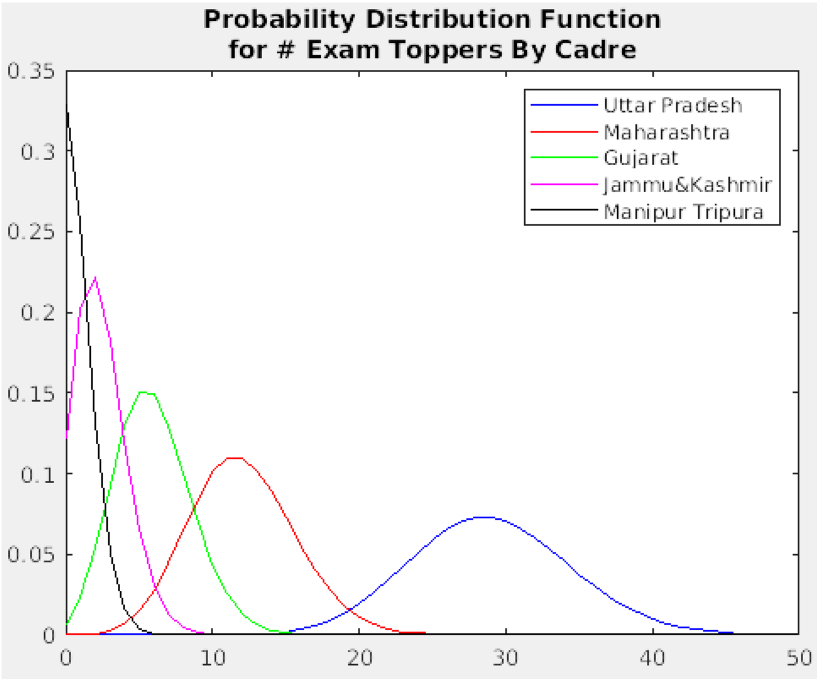
Notes: Figures from Benbabaali (2008), showing the occurrence rate of the cadres among the 5 *most preferred* cadres (*Left*) and the 5 *least preferred* cadres (*Right*). The responses are from Benbabaali's representative sample survey of IAS officers of an unspecified (for anonymity) batch between 2003 and 2006. Notice that bad cadres are consistently preferred amongst the 5 least preferred cadres and seem to rarely be top preference of IAS officers.

Figure 14. Distribution of cadre preferences of Candidates from UP.



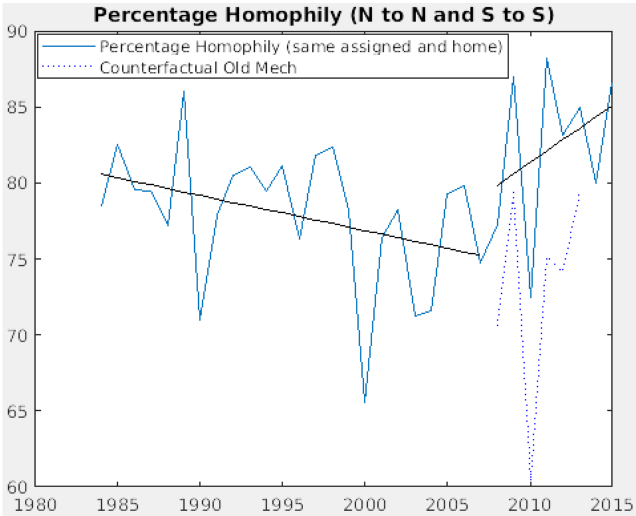
Notes: Maps show the distribution of cadre preferences across 4 quartiles for all 18 IPS officers from Uttar Pradesh in 2008.

Figure 15. Estimated probability distribution function for exam toppers for selected cadres.



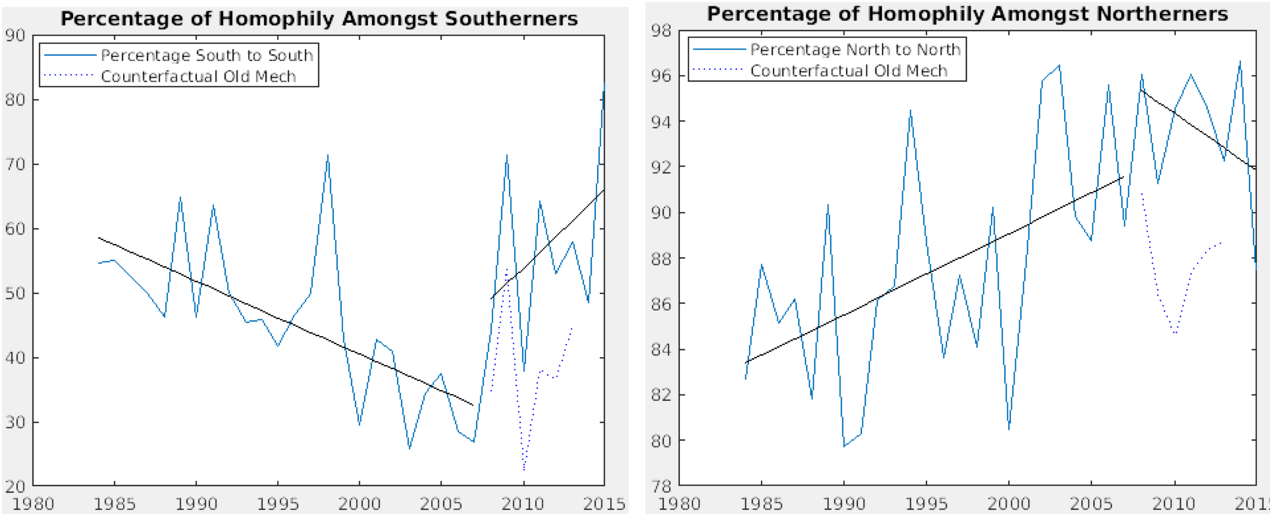
Notes: Using 2013 poisson regression coefficients for Uttar Pradesh ($\hat{\lambda} = 29.98$), Maharashtra ($\hat{\lambda} = 13.85$), Gujarat ($\hat{\lambda} = 6.95$), Jammu and Kashmir ($\hat{\lambda} = 3.29$), and Manipur Tripura ($\hat{\lambda} = 1.55$) from poisson regression in Table 8, we see a large heterogeneity in the ability to place exam toppers across various cadres.

Figure 16. Percentage of Homophily: Northerners assigned to Northern Cadres and Southerners assigned to Southern Cadres.



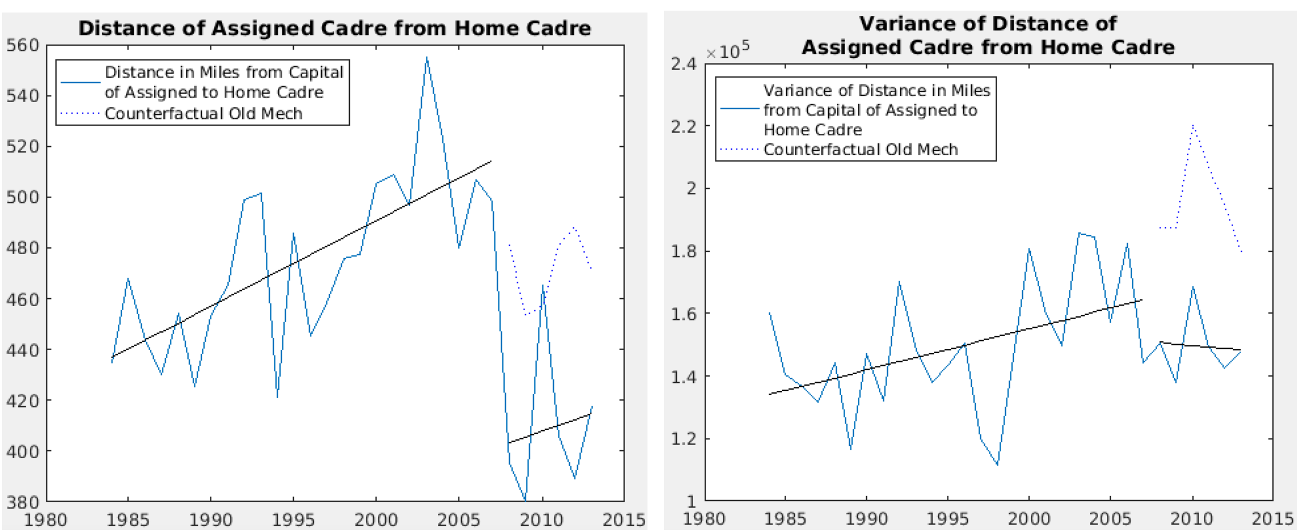
Notes: The solid blue line shows the actual assignment data, the dotted line is the simulated counterfactual using the Old Mechanism for years 2008 onwards, and the solid black lines show trends for 1984-2007 and 2008 onwards. We notice an increase in regional homophily under the New Mechanism.

Figure 17. Homophily amongst Northerners and amongst Southerners.



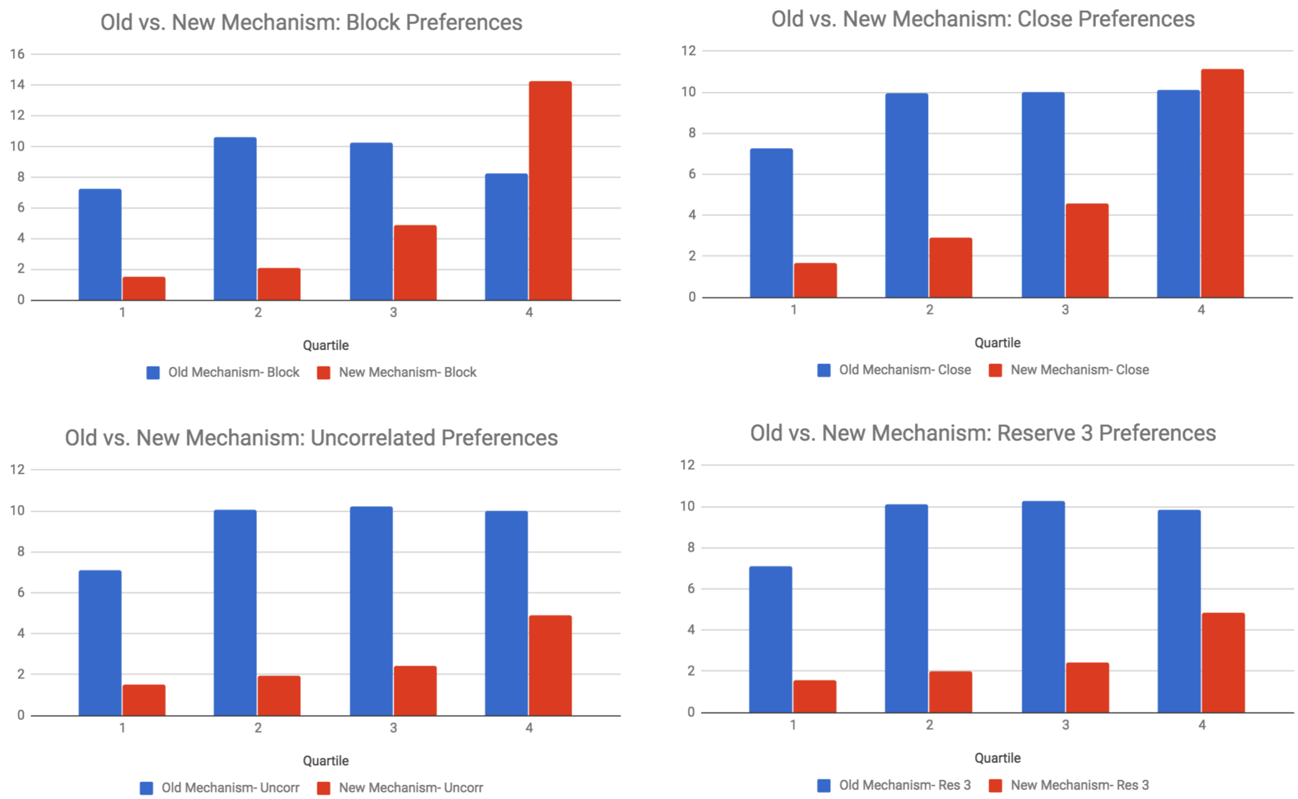
Notes: *Left*: Percentage of Southerners assigned to Southern Cadres. *Right*: Percentage of Northerners assigned to Northern Cadres. The solid blue line shows the actual assignment data, the dotted line is the simulated counterfactual using the Old Mechanism for years 2008 onwards, and the solid black lines show trends for 1984-2007 and 2008 onwards. We notice an increase in regional homophily for both Southerners and Northerners with the New Mechanism.

Figure 18. Old vs. New Mechanism effect on Distance of Assigned Cadre from Home Cadre.



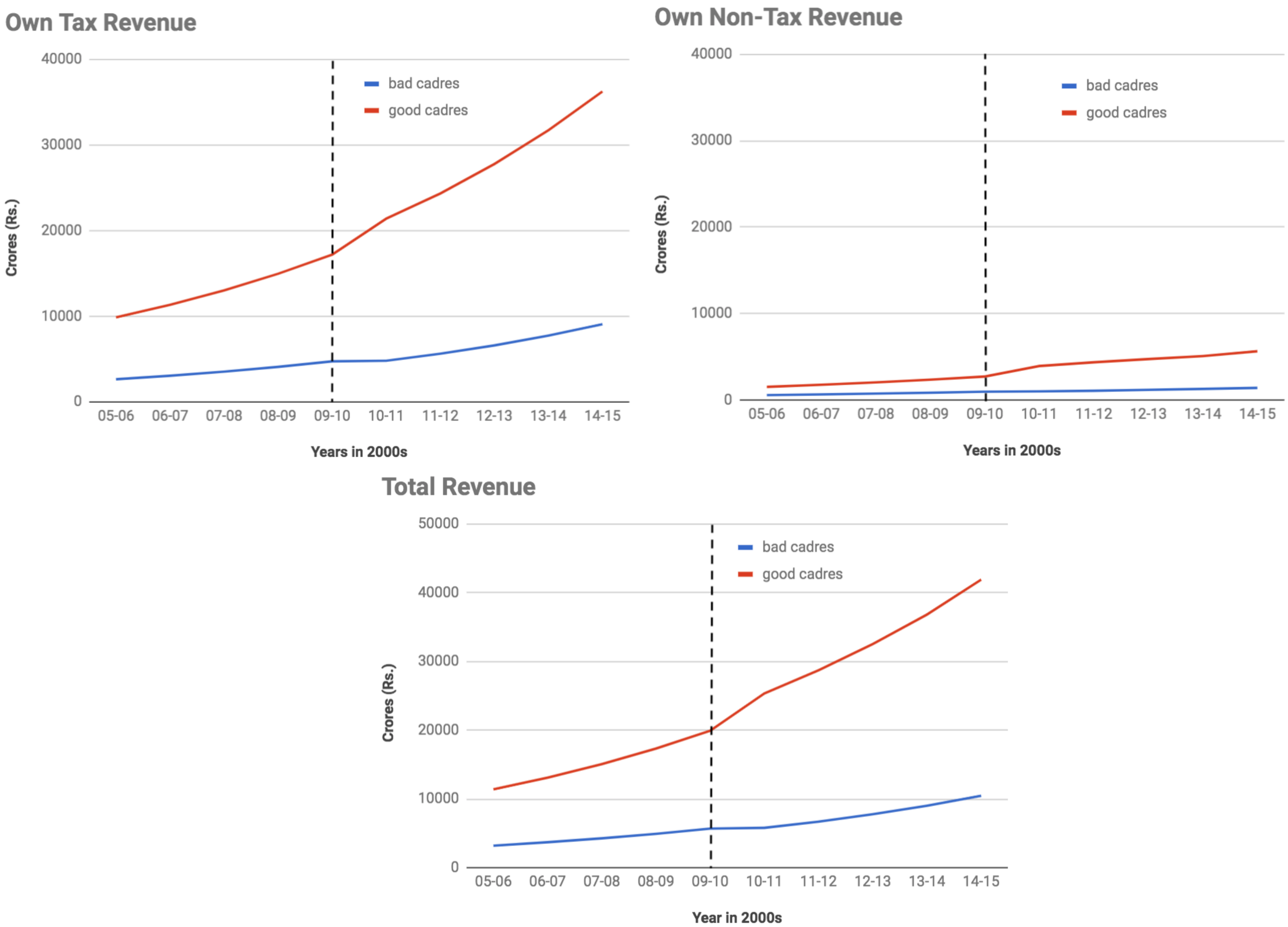
Notes: Mean (*Left*) and variance (*Right*) of distance from assigned cadre to home cadre across candidates by year. Distances are measured by miles between capitals. The solid blue line shows the actual assignment data, the dotted line is the simulated counterfactual using the Old Mechanism for years 2008 onwards, and the solid black lines show trends for 1984-2007 and 2008 onwards. We notice that with the New Mechanism, candidates are assigned to cadres closer to their home state and variance of distance also falls.

Figure 19. Average preference rank for each exam quartile with Old vs. New Mechanism under various preference structures.



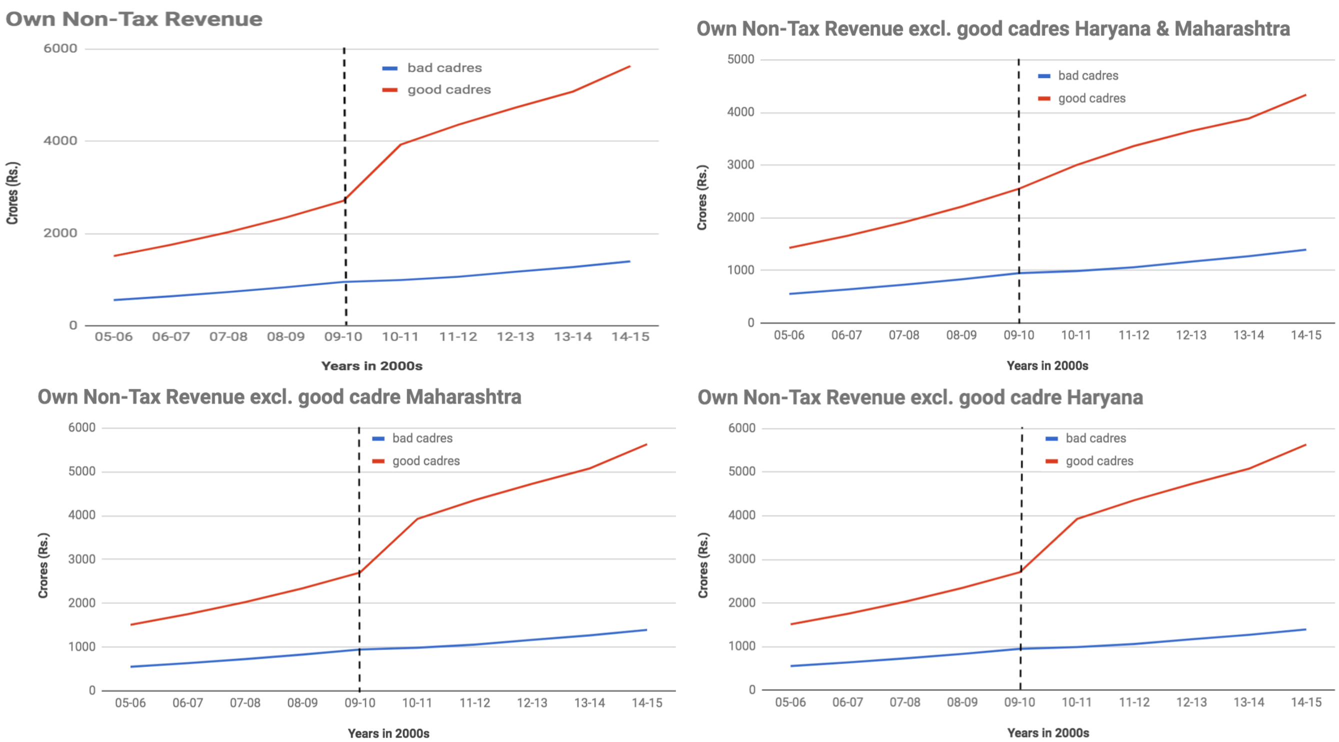
Notes: *Top Left*: block preferences, *Top Right*: preference by closeness in distance, *Bottom Left*: uncorrelated preferences, and *Bottom Right*: reserve 3 preferences. Notice that with minimal correlation (uncorrelated and reserve 3 preferences), all quartiles are better off with the New Mechanism. However, with sufficiently high correlation in preferences (block and close preferences), the 4th quartile is worse off with the New Mechanism because highly sought-after vacancies fill up early. Simulations run on data from years 2005 to 2013.

Figure 20. Old vs. New Mechanism effect on Tax Revenues.



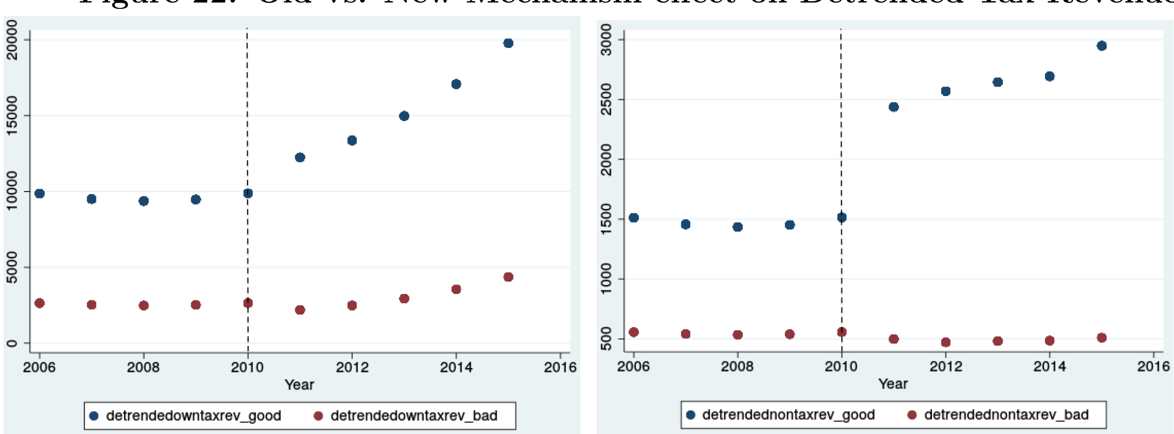
Notes: Own tax revenues (*Top Left*) and Non-tax revenues (*Top Right*), and Total revenues= own tax + non-tax (*Bottom*) amongst bad and good cadres for fiscal years 2005-06 to 2014-15. Fiscal year 2010-11 onwards fall under New Mechanism. We see a divergence between good and bad cadres from 2011 onwards fall under New Mechanism. Note that the jump in the Own Non-Tax Revenue occurs due to Haryana and Maharashtra; see Figure 21 for robustness.

Figure 21. Robustness: Old vs. New Mechanism effect on Tax Revenues.



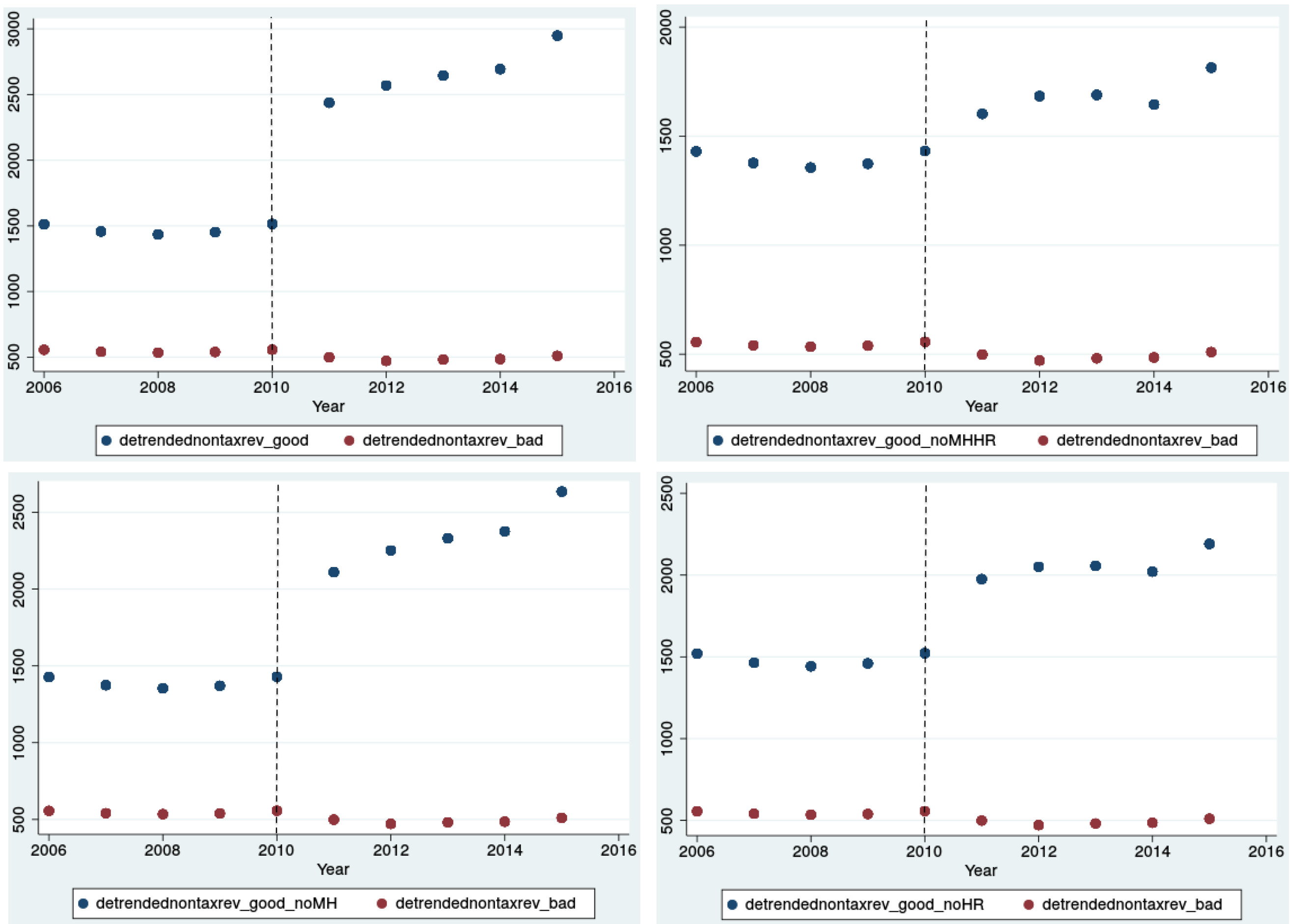
Notes: The non-tax revenue graph from Figure 20 appears misleading in that good cadres appear to have done better with a jump in year 2010-11 and onwards, but this is attributed to jumps in non-tax revenue only in Haryana and Maharashtra. We show the graphs with all data (*Top Left*), excluding Maharashtra and Haryana (*Top Right*), excluding only Maharashtra (*Bottom Left*), and excluding only Haryana (*Bottom Right*). In Table 24, we show the robustness of the results to these exclusions. All coefficients on non-tax revenues appear insignificant regardless whether we include or exclude these cadres.

Figure 22. Old vs. New Mechanism effect on Detrended Tax Revenues.



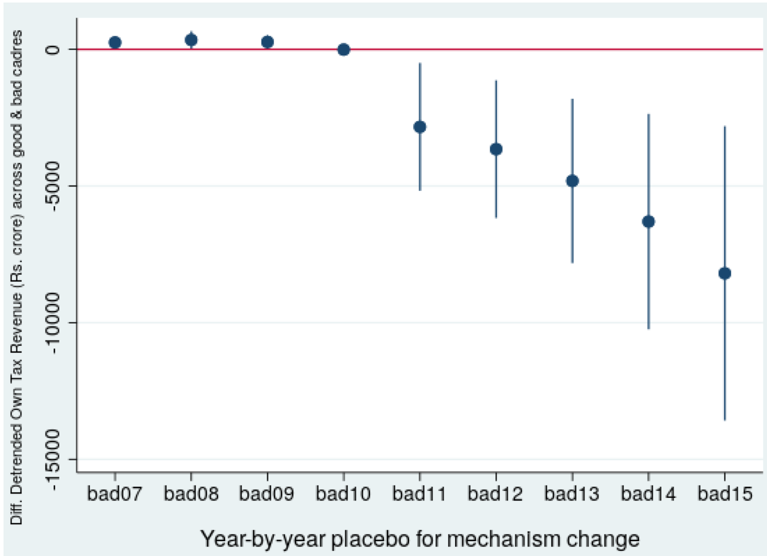
Notes: Detrended Own Tax Revenue (*Left*) and Detrended Non-tax Revenue (*Right*) for years 2005-06 to 2014-15 (IAS batches 2005-2012). Fiscal year 2010-11 onwards fall under New Mechanism. We see a divergence between good and bad cadres from 2011 onwards fall under New Mechanism. Note that the jump in Own Non-Tax Revenue occurs due to Haryana and Maharashtra; see Figure 23 for robustness.

Figure 23. Robustness: Old vs. New Mechanism effect on Detrended Tax Revenues.



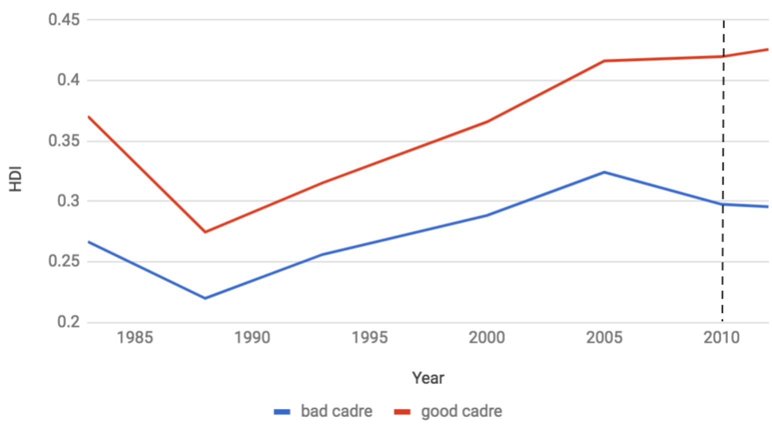
Notes: The detrended non-tax revenue graph from Figure 22 appears misleading in that good cadres appear to have done better with a jump in year 2010-11 and onwards, but this is attributed to jumps in non-tax revenue only in Haryana and Maharashtra. We show the detrended graphs with all data (*Top Left*), excluding Maharashtra and Haryana (*Top Right*), excluding only Maharashtra (*Bottom Left*), and excluding only Haryana (*Bottom Right*). In Table 24, we show the robustness of the results to these exclusions. All coefficients on non-tax revenues appear insignificant regardless whether we include or exclude these cadres.

Figure 24. Placebo Test: Year-by-year placebo tests for change of mechanism on detrended own tax revenue.



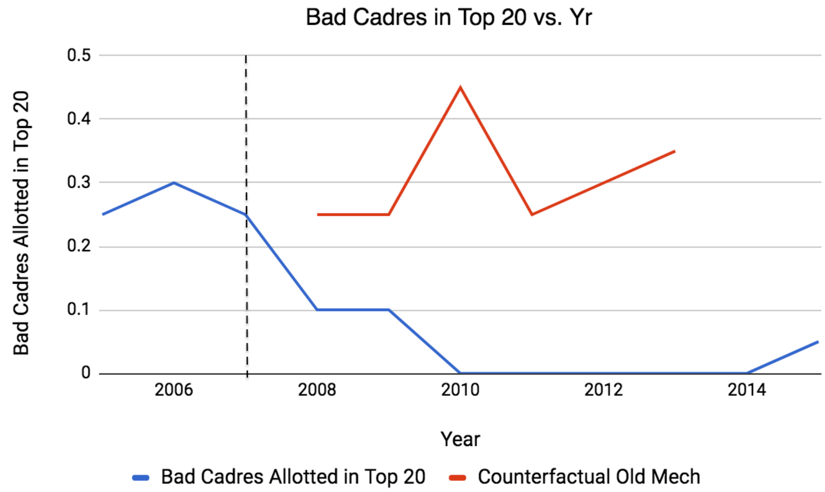
Notes: This figure plots the year-by-year placebo tests for change of mechanism on the difference in detrended own tax revenue across good and bad cadres, from Table 11. We see that under the Old Mechanism years (last batch of 2007 affected the 2009-10 fiscal year, labeled bad10), the estimates are small, precise, and near zero; whereas, under the New Mechanism years (first batch of 2008 affected the 2010-11 fiscal year, labeled bad11), difference between good and bad cadres' detrended own tax revenue is away large, negative, and has 95% confidence intervals away from zero.

Figure 25. Human Development Index across good and bad cadres.



Notes: Plotting Human Development Index grouped by good and bad cadres from 1983 to 2012. Data used is HDI for years 1983, 1988, 1993, 2000, 2005, 2010, and 2012 constructed by Mukherjee et al. (2014). We observe a divergence in HDI across the good and bad cadres from 2010 onwards (data for years 2010 and 2012) when the IAS officers from the post-2008 New Mechanism start working.

Figure 26. Percentage of top 20 exam toppers being assigned to bad cadres.



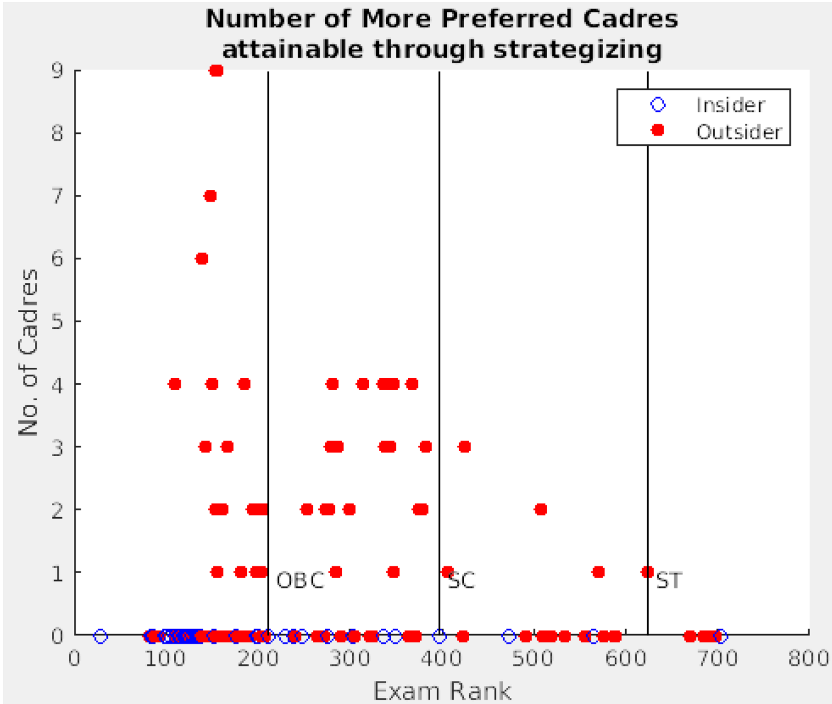
Notes: The blue line is the actual assignment data and red line is the simulated counterfactual using the Old Mechanism for years 2008 onwards. Since 7 out of 24 cadres are bad, a uniform distribution of exam toppers would be around 30%. We see a big drop starting with the New Mechanism in 2008.

Figure 27. Comparing requests for insiders vs. number of insiders assigned.

Requests				Assignments			
2005-2007		2008-2013		2005-2007		2008-2013	
State	Ratio	State	Ratio	State	Ratio	State	Ratio
Himachal Pr	0.25	Punjab	0.31	Himachal Pra	0.00	Nagaland	0.00
Sikkim	0.25	Jammu & Ka	0.32	Sikkim	0.00	Sikkim	0.00
Uttarakhand	0.25	Nagaland	0.32	Chhattisgarh	0.06	West Bengal	0.10
Bihar	0.29	Orissa	0.32	Assam Megh	0.07	Uttarakhand	0.11
Gujarat	0.29	Karnataka	0.33	Gujarat	0.12	Chhattisgarh	0.14
Maharashtra	0.29	Andhra Prad	0.33	Nagaland	0.13	Assam Megh	0.16
Rajasthan	0.30	Chhattisgarh	0.33	Manipur Trip	0.20	Gujarat	0.18
Uttar Prades	0.32	Gujarat	0.33	Uttarakhand	0.25	Manipur Trip	0.21
A G M U T	0.33	Tamil Nadu	0.33	West Bengal	0.27	Madhya Prac	0.24
Assam Megh	0.33	Uttar Prades	0.33	Bihar	0.29	Orissa	0.24
Chhattisgarh	0.33	Uttarakhand	0.33	Madhya Prac	0.29	Jharkhand	0.26
Haryana	0.33	West Bengal	0.33	Maharashtra	0.29	Karnataka	0.28
Jammu & Ka	0.33	Madhya Pra	0.34	Rajasthan	0.30	A G M U T	0.29
Jharkhand	0.33	A G M U T	0.34	Uttar Prades	0.32	Punjab	0.31
Kerala	0.33	Maharashtra	0.34	A G M U T	0.33	Himachal Pra	0.32
Manipur Trip	0.33	Assam Megh	0.34	Haryana	0.33	Jammu & Ka	0.32
Tamil Nadu	0.33	Jharkhand	0.34	Jammu & Ka	0.33	Andhra Prad	0.33
West Bengal	0.33	Rajasthan	0.34	Jharkhand	0.33	Tamil Nadu	0.33
Madhya Pra	0.35	Haryana	0.35	Kerala	0.33	Uttar Prades	0.34
Karnataka	0.36	Bihar	0.35	Tamil Nadu	0.33	Maharashtra	0.34
Punjab	0.36	Kerala	0.35	Karnataka	0.36	Rajasthan	0.34
Nagaland	0.38	Manipur Trip	0.37	Punjab	0.36	Haryana	0.35
Orissa	0.38	Himachal Pr	0.37	Orissa	0.38	Bihar	0.35
Andhra Prad	0.43	Sikkim	0.43	Andhra Prad	0.43	Kerala	0.35

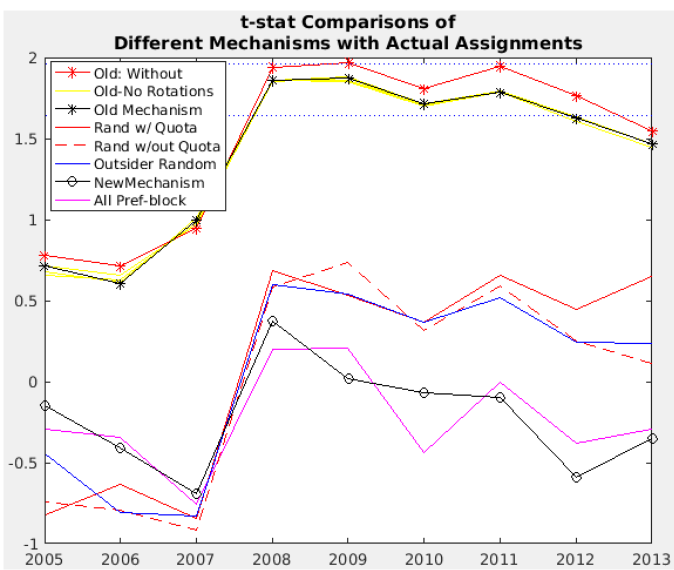
Notes: *Left*: fraction of insider requests by cadre. *Right*: fraction of insiders allotted to each cadre. Notice that requests are around .33 given the 1:2 target between insiders and outsiders; however, assignments which signify the ability to meet this target vary vastly across states. Analysis separated into years 2005-07 (Old Mechanism) and 2008-13 (New Mechanism).

Figure 28. Susceptibility of the 2017 Mechanism to Strategic Behavior.



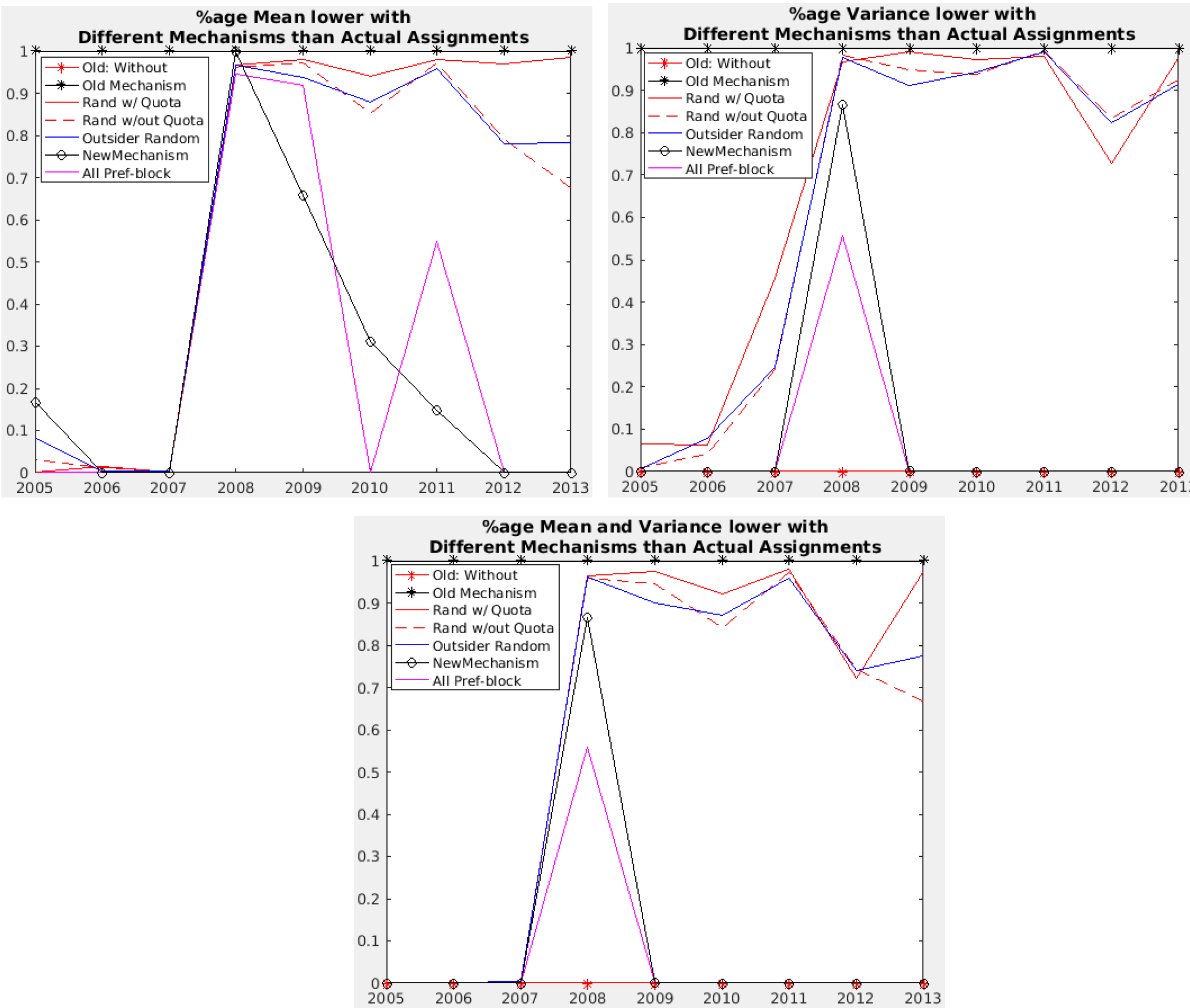
Notes: Assuming all agents $-i$ report their preferences truthfully, this figure shows, for each individual i, how many cadres there are which i can get via strategic reporting and which he strictly prefers to the cadre he achieves via truthful reporting. Notice those who are assigned insider positions (blue) cannot improve, whereas amongst those assigned outsider positions (red), relatively lower ranked individuals within each quota category can improve via strategic reporting. And those with lower exam rank can only achieve fewer possible improvements due to competition arising from correlated preferences. Data used for simulation is from IPS 2008 batch.

Figure 29. Simulations to Test Path of One-sided Mechanisms 1.



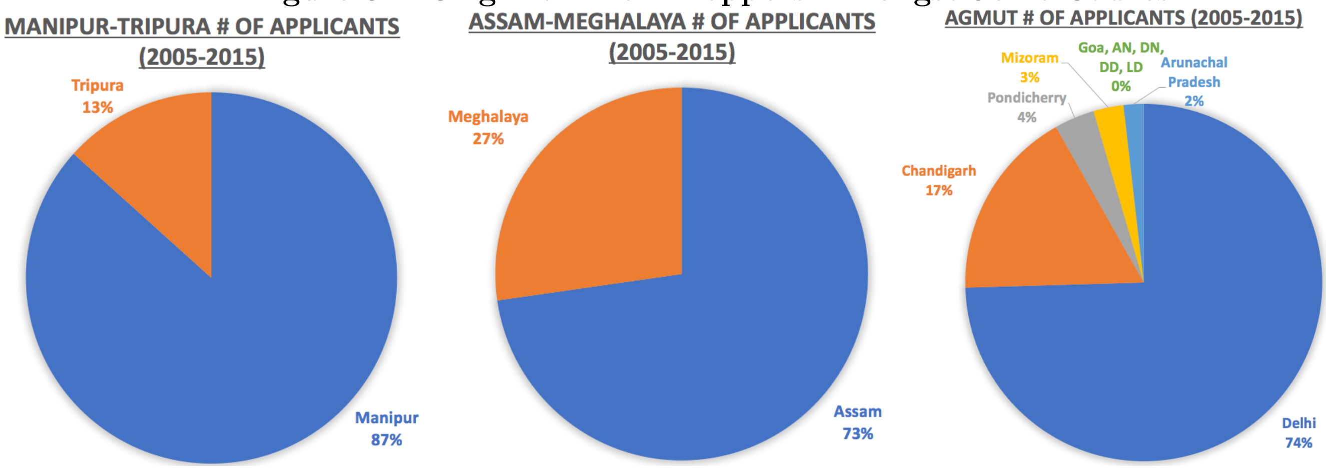
Notes: t-statistic comparisons of various simulated mechanisms with actual assignments. We notice that the ranking of one-sided cadre allocation mechanisms from Section 6.3 approximately holds in the data.

Figure 30. Simulations to Test Path of One-sided Mechanisms 2.



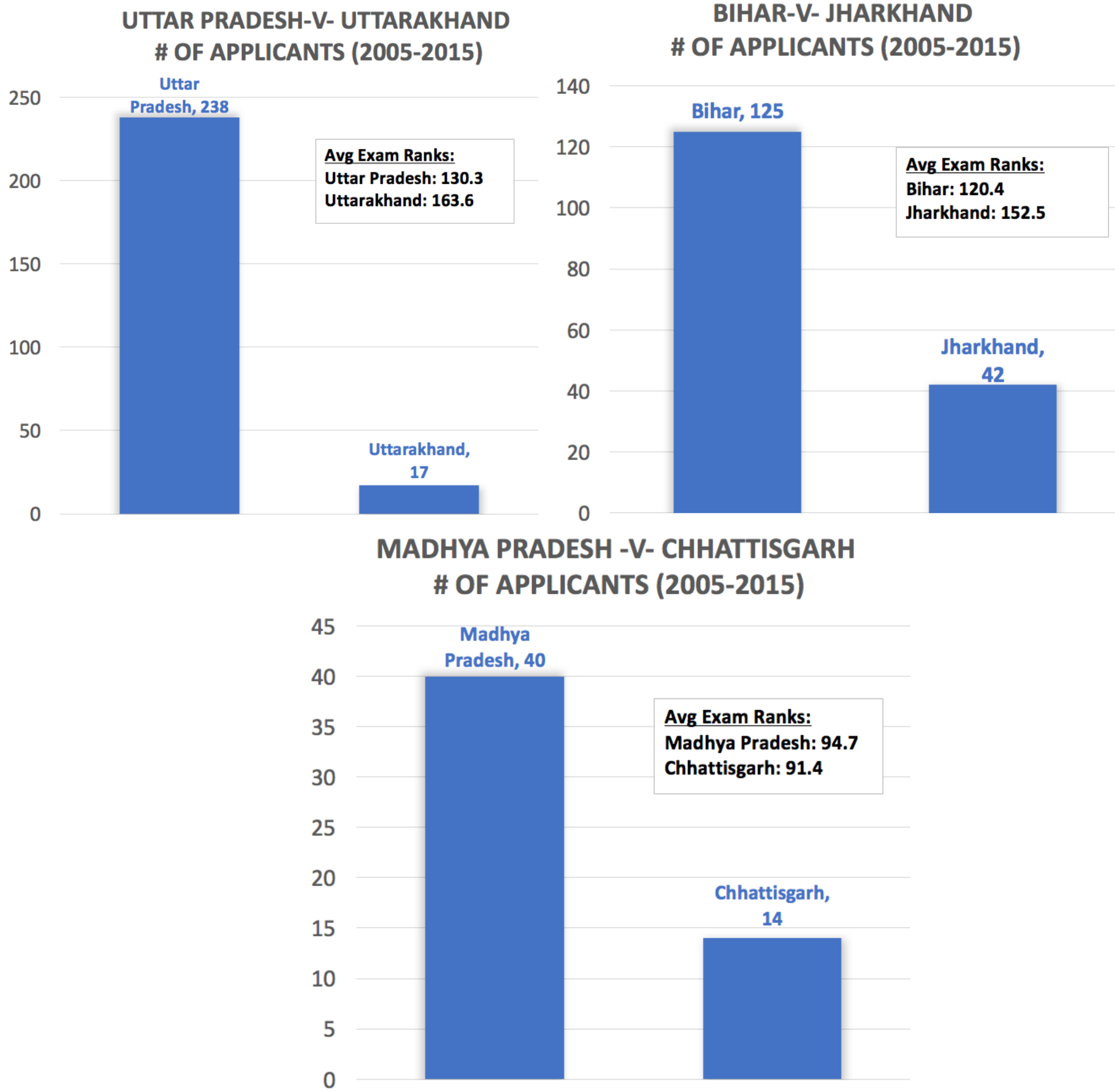
Notes: *Top Left*: percent of across-cadre mean of average exam rank by cadre which are lower in the simulated mechanism than in the actual assignments. *Top Right*: percent of across-cadre variance of average exam rank by cadre which are lower in the simulated mechanism than in the actual assignments. *Bottom*: percent of across-cadre mean and variance lower in the simulated mechanism than in the actual assignments. We notice that the ranking of one-sided cadre allocation mechanisms from Section 6.3 approximately holds in the data.

Figure 31. Origin of Exam Toppers Amongst Joint Cadres.



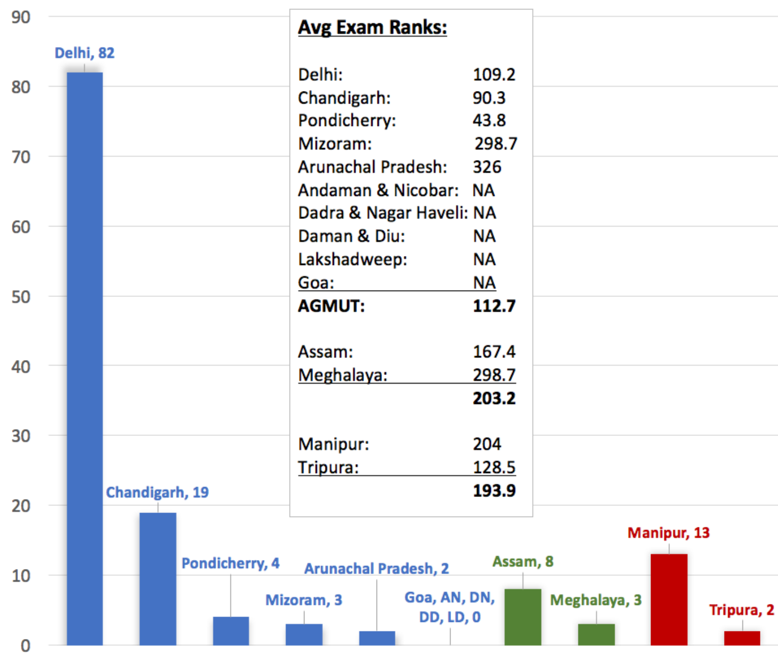
Notes: Proportion of exam toppers coming from each state/territory in Joint Cadres (Manipur-Tripura and Assam-Meghalaya) and Grouped Cadre (AGMUT).

Figure 32. Exam toppers from States which split in 2000.



Notes: Number and average exam ranks of exam toppers coming from each cadre in the new states formed in 2000 relative to their mother states: Uttarakhand, Jharkhand, and Chhattisgarh.

Figure 33. Origin and Average Exam Rank of Exam Toppers from Joint Cadres.



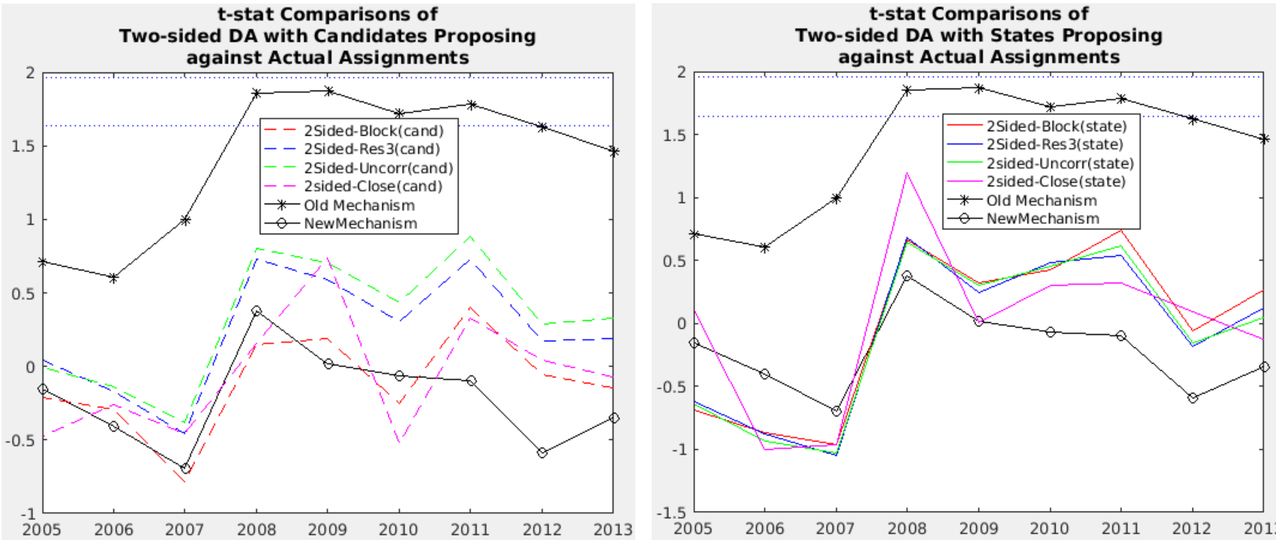
Notes: Number and average exam rank of exam toppers from Joint Cadres (Manipur-Tripura and Assam-Meghalaya) and Grouped Cadre (AGMUT).

Figure 34. Average exam rank of assigned candidates by cadre.

2005-2007		2008-2013		2014-2015	
State	**Exam Rank**	**State**	**Exam Rank**	**State**	**Exam Rank**
Jharkhand	38.4	Haryana	78.4	Rajasthan	95.0
Sikkim	39.0	Karnataka	86.8	Maharashtra	128.6
Andhra Pradesh	47.3	Andhra Pradesh	87.5	A G M U T	134.6
Orissa	53.8	Madhya Pradesh	96.7	Gujarat	139.0
Rajasthan	60.2	Tamil Nadu	105.2	Madhya Pradesh	141.0
Assam Meghalaya	61.1	Uttarakhand	109.5	Andhra Pradesh	145.8
Uttarakhand	62.9	Punjab	110.8	Orissa	152.2
Haryana	68.7	Rajasthan	112.3	Tamil Nadu	156.3
Tamil Nadu	71.4	A G M U T	113.1	West Bengal	160.8
Manipur Tripura	72.7	Gujarat	118.7	Kerala	174.4
Nagaland	73.8	Maharashtra	121.1	Karnataka	176.6
A G M U T	74.2	Uttar Pradesh	123.4	Punjab	185.8
Maharashtra	76.7	Bihar	142.2	Telangana	212.2
Himachal Pradesh	78.2	Orissa	143.6	Jammu & Kashmir	224.9
Punjab	78.7	Kerala	149.1	Uttar Pradesh	226.2
Bihar	79.7	Jharkhand	160.8	Himachal Pradesh	233.0
Madhya Pradesh	79.9	Sikkim	189.9	Bihar	278.9
Kerala	81.2	West Bengal	195.6	Haryana	289.1
Jammu & Kashmir	86.6	Jammu & Kashmir	196.5	Assam Meghalaya	295.2
Chhattisgarh	90.3	Chhattisgarh	197.8	Chhattisgarh	308.7
West Bengal	92.2	Himachal Pradesh	206.0	Jharkhand	309.2
Karnataka	96.8	Assam Meghalaya	250.5	Manipur	317.5
Gujarat	113.9	Nagaland	279.3	Uttarakhand	321.4
Uttar Pradesh	144.0	Manipur Tripura	322.2	Tripura	455.3
				Sikkim	510.0
				Nagaland	543.6

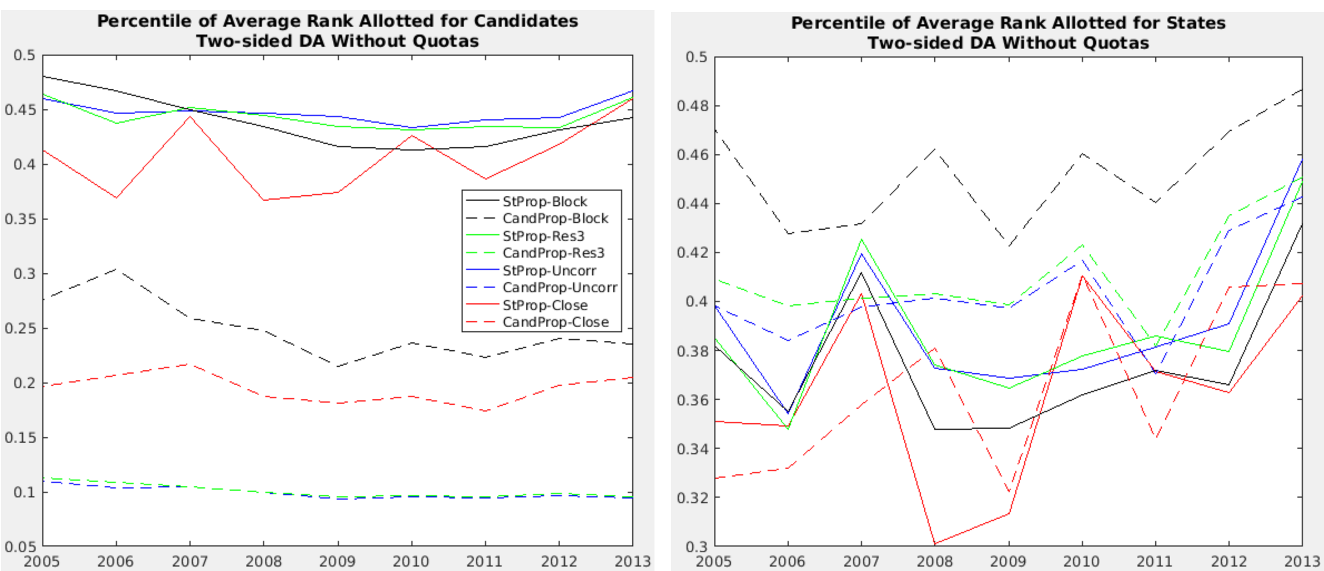
Notes: Highlighted entries show the impact of Andhra Pradesh splitting up into Andhra Pradesh and Telangana in 2014. Analysis separated into years 2005-07 (Old Mechanism), 2008-13 (New Mechanism), and 2014-15 (New Mechanism with new states).

Figure 35. Comparing Two-sided DA with Actual Assignments.



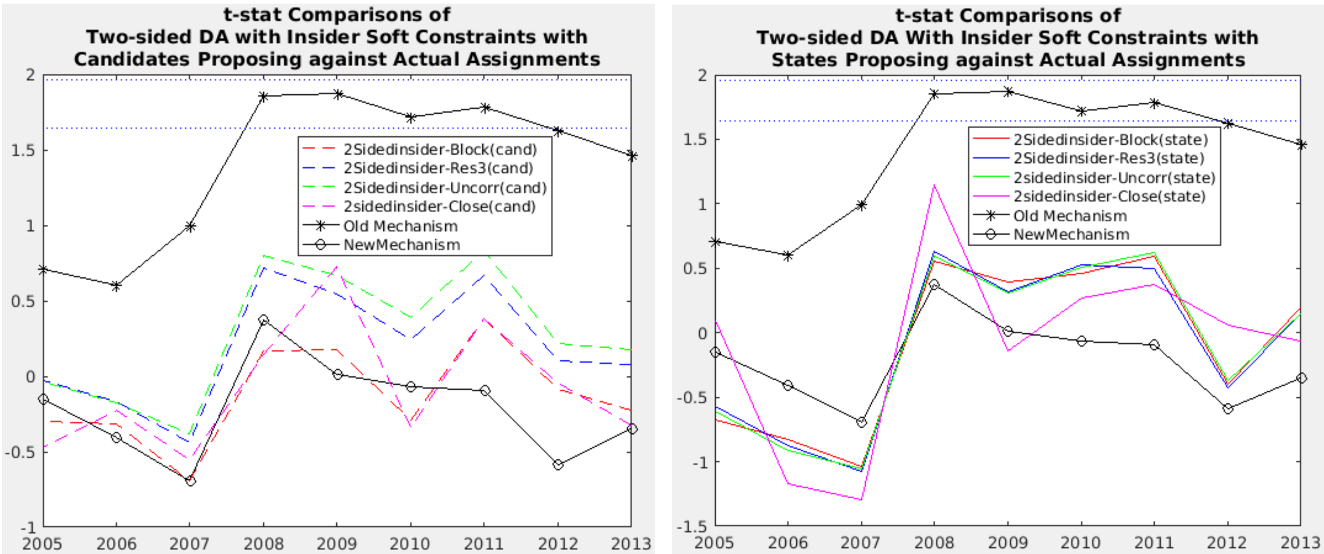
Notes: t-statistic comparing candidate-proposing (*Left*) and cadre-proposing (*Right*) Deferred Acceptance using various simulated preferences to Actual Assignments. Simulations for block (red), reserve 3 (blue), uncorrelated (green), and close preferences (purple). Includes simulated Old and New Mechanisms for comparison.

Figure 36. Percentile of average preference rank allotted under Two-sided DA.



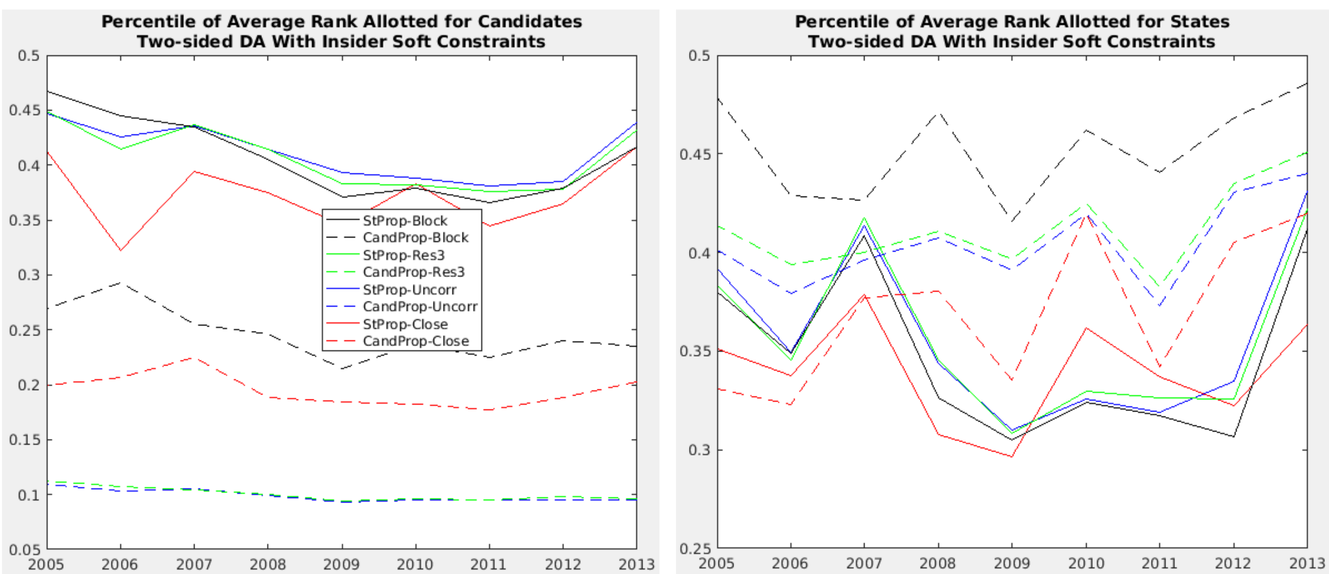
Notes: Percentile of average preference rank of assignment for candidates (*Left*) and states (*Right*) with Deferred Acceptance. Simulations for block (black), reserve 3 (green), uncorrelated (blue), and close preferences (red).

Figure 37. Comparing Two-sided DA with insider soft constraints with Actual Assignments.



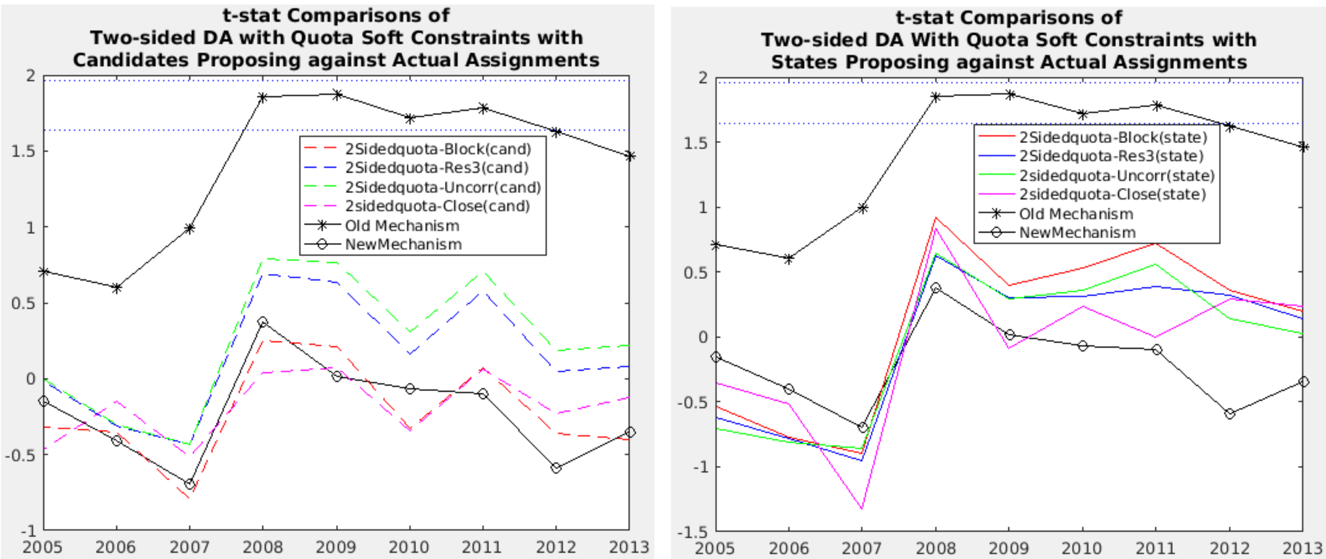
Notes: t-statistic comparing candidate-proposing (*Left*) and cadre-proposing (*Right*) Deferred Acceptance with insider soft constraints and various simulated preferences to Actual Assignments. Simulations for block (red), reserve 3 (blue), uncorrelated (green), and close preferences (purple). Includes simulated Old and New Mechanisms for comparison.

Figure 38. Percentile of average preference rank allotted under Two-sided DA with insider soft constraints.



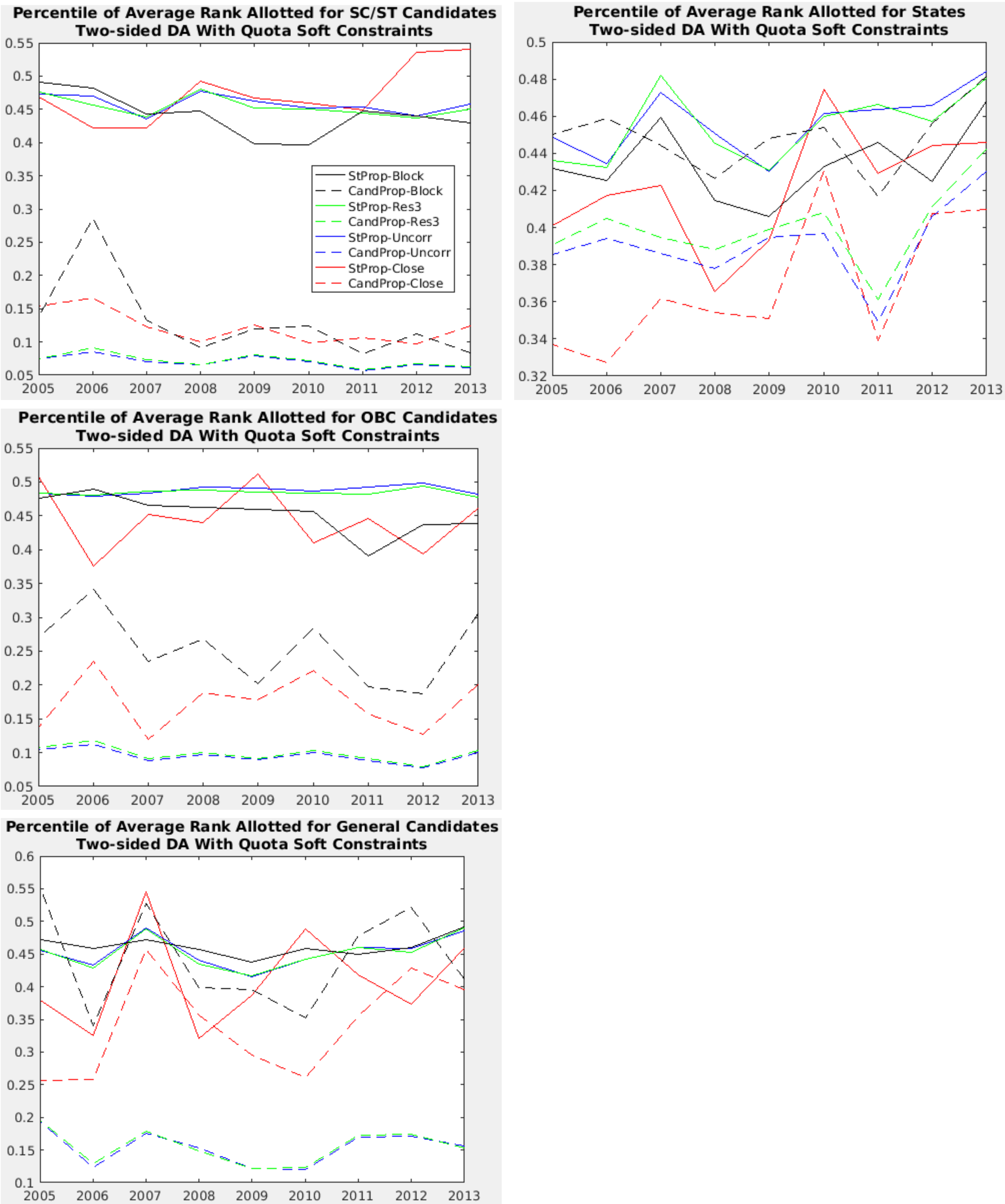
Notes: Percentile of average preference rank of assignment for candidates (*Left*) and states (*Right*) with Deferred Acceptance with insider soft constraints. Simulations for block (black), reserve 3 (green), uncorrelated (blue), and close preferences (red).

Figure 39. Comparing Two-sided DA with quota soft constraints with Actual Assignments.



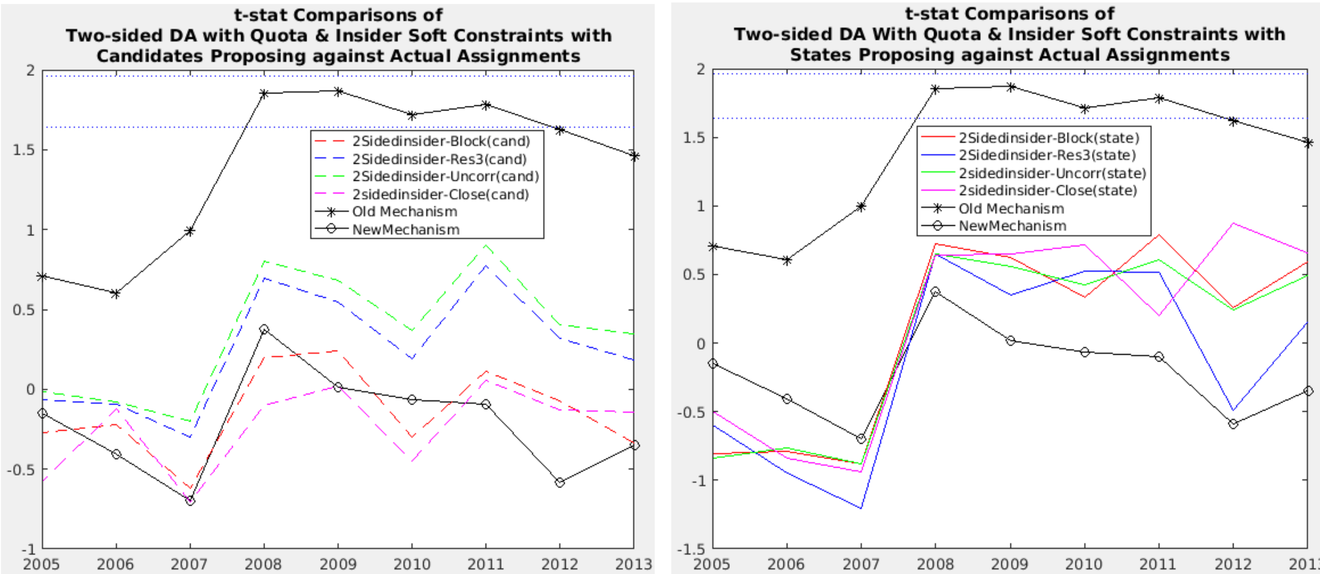
Notes: t-statistic comparing candidate-proposing (*Left*) and cadre-proposing (*Right*) Deferred Acceptance with quota soft constraints and various simulated preferences to Actual Assignments. Simulations for block (red), reserve 3 (blue), uncorrelated (green), and close preferences (purple). Includes simulated Old and New Mechanisms for comparison.

Figure 40. Percentile of average preference rank allotted under Two-sided DA with quota soft constraints.



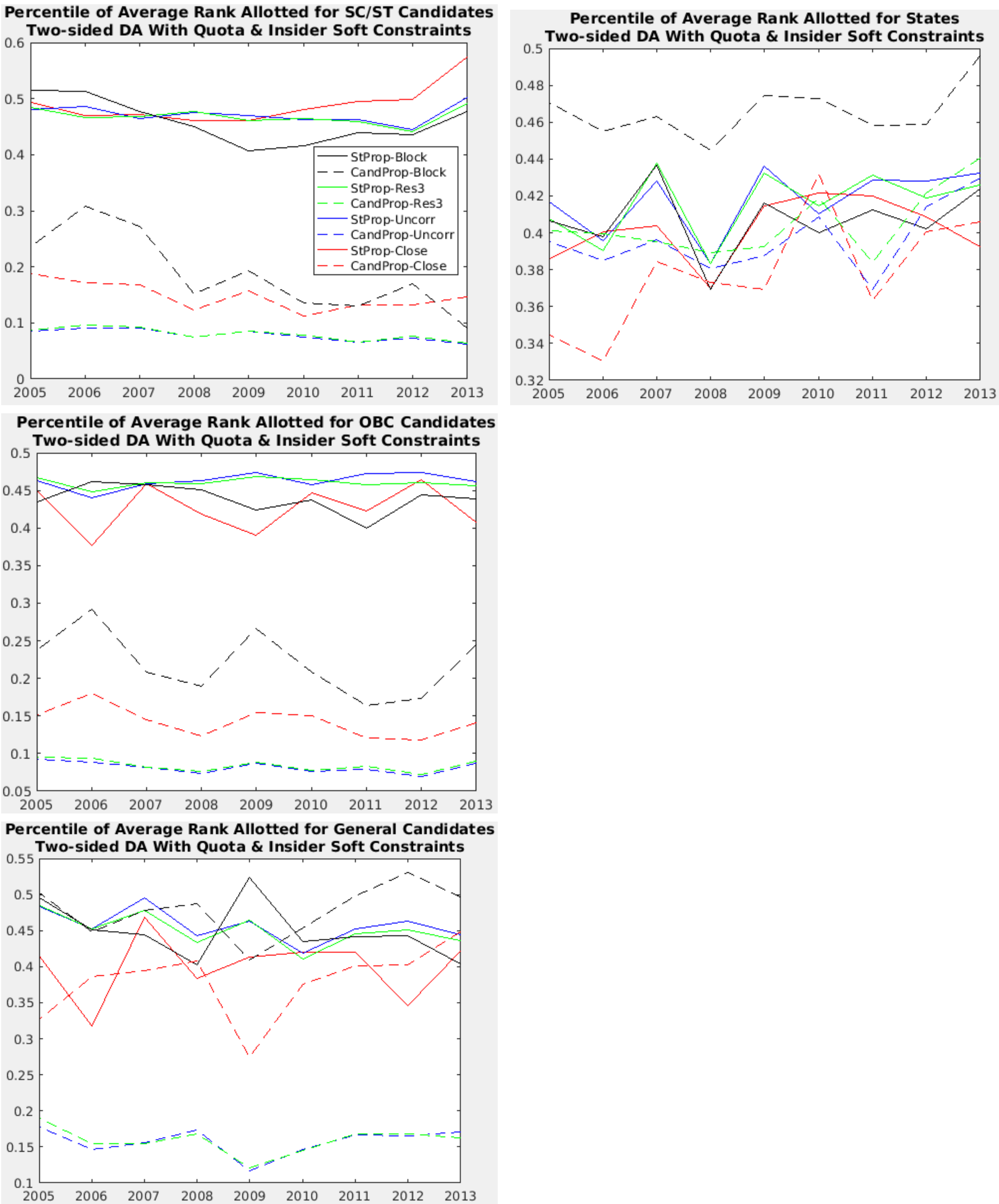
Notes: Percentile of average preference rank of assignment for candidates (*Left*) and states (*Right*) with Deferred Acceptance with quota soft constraints. Candidate performance is split by SC/ST category (*Top*), OBC category (*Middle*), and General category (*Bottom*). Solid (dashed) lines have states (candidates) proposing. Simulations for block (black), reserve 3 (green), uncorrelated (blue), and close preferences (red).

Figure 41. Comparing Two-sided DA with quota x insider soft constraints with Actual Assignments.



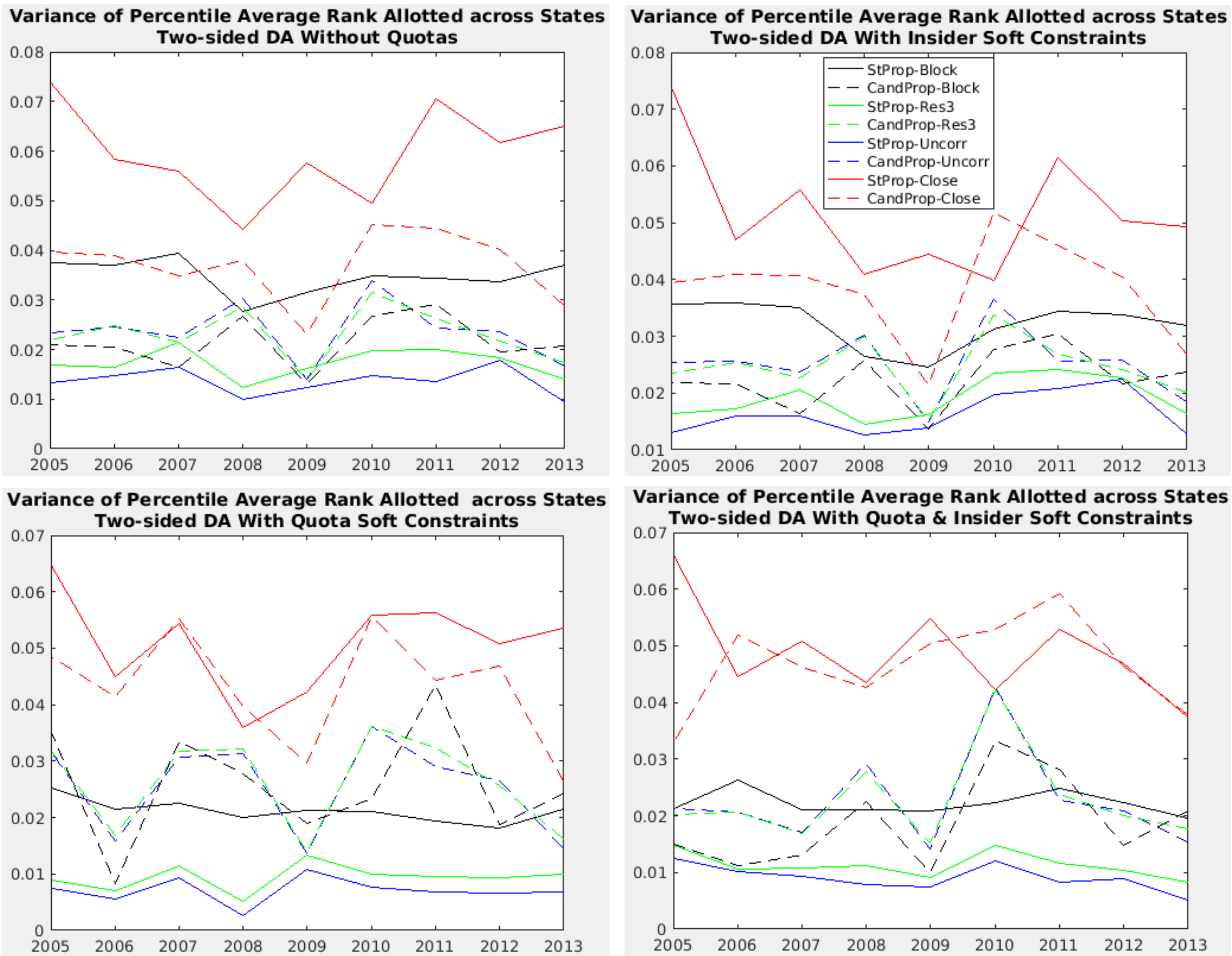
Notes: t-statistic comparing candidate-proposing (*Left*) and cadre-proposing (*Right*) Deferred Acceptance with quota x insider soft constraints and various simulated preferences to Actual Assignments. Simulations for block (red), reserve 3 (blue), uncorrelated (green), and close preferences (purple). Includes simulated Old and New Mechanisms for comparison.

Figure 42. Percentile of average preference rank allotted under Two-sided DA with quota x insider soft constraints.



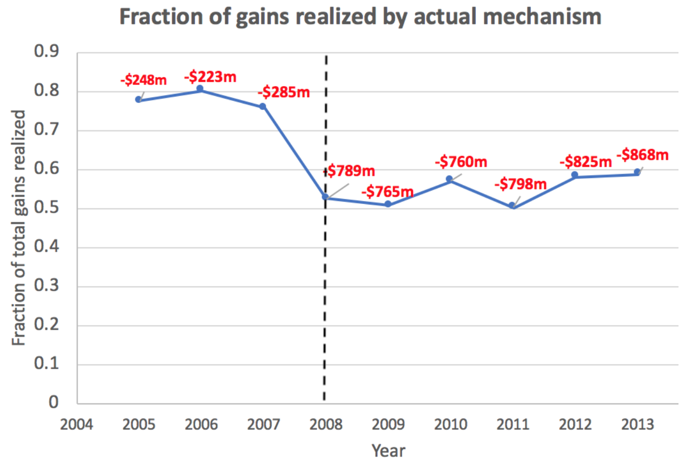
Notes: Percentile of average preference rank of assignment for candidates (*Left*) and states (*Right*) with Deferred Acceptance with quota x insider soft constraints. Candidate performance is split by SC/ST category (*Top*), OBC category (*Middle*), and General category (*Bottom*). Solid (dashed) lines have states (candidates) proposing. Simulations for block (black), reserve 3 (green), uncorrelated (blue), and close preferences (red).

Figure 43. Variance of percentile average preference rank for DA with and without soft constraints.



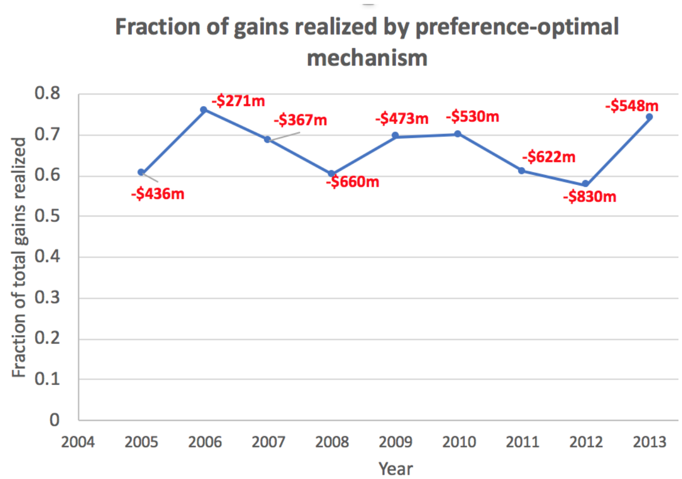
Notes: Variance of percentile average preference rank of assigned candidates across cadres for Deferred Acceptance with no reservations (*Top Left*), Deferred Acceptance with insider soft constraints (*Top Right*), Deferred Acceptance with quota soft constraints (*Bottom Left*), and Deferred Acceptance with quota x insider soft constraints (*Bottom Right*). Solid (dashed) lines have states (candidates) proposing. Simulations for block (black), reserve 3 (green), uncorrelated (blue), and close preferences (red).

Figure 44. Fraction of Gains in Own Tax Revenue Realized by Actual Mechanism.



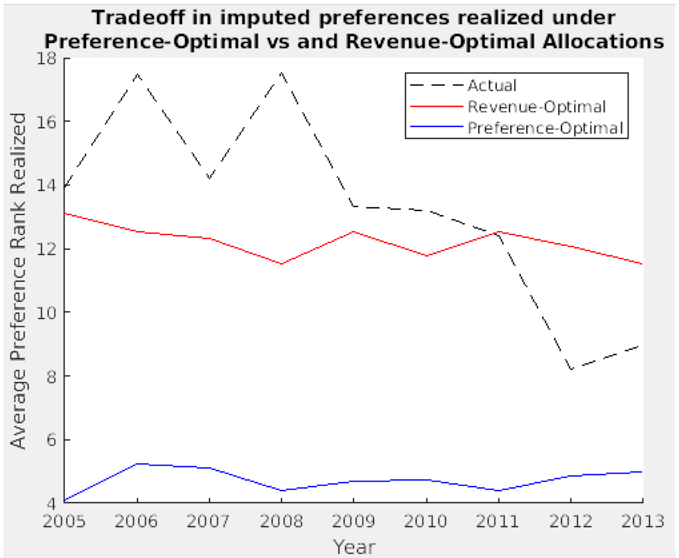
Notes: This figure plots the percentage of total gains in own tax revenues (max minus least own tax revenue counterfactuals) and shows the dollar value of this revenue loss under the actual mechanisms used.

Figure 45. Fraction of Gains in Own Tax Revenue Realized with the Preference-Optimal Allocation.



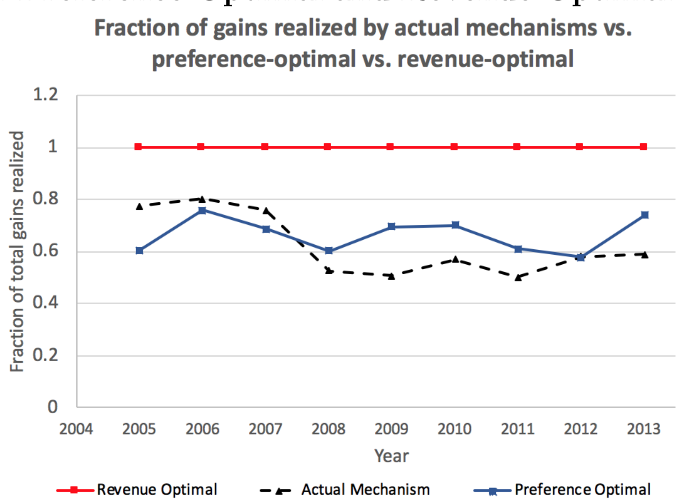
Notes: This figure plots the percentage of total gains in own tax revenues (max minus least own tax revenue counterfactuals) and shows the dollar value of this revenue loss for a counterfactual allocation that minimized average preference rank assigned.

Figure 46. Trade-off in Preferences Under Preference-Optimal and Revenue-Optimal Allocations.



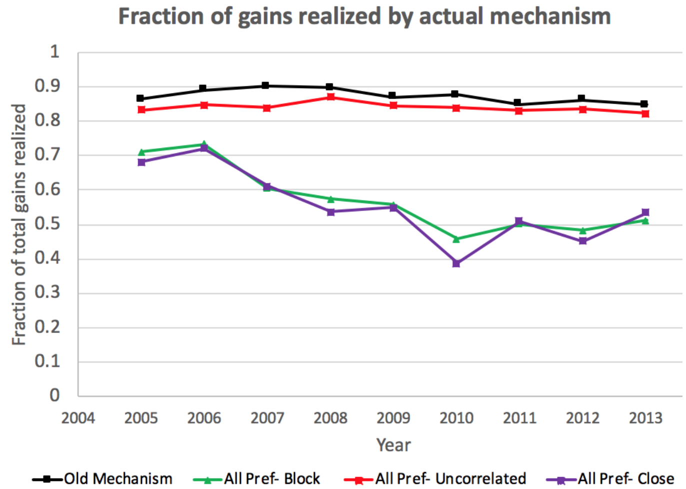
Notes: This figure plots the average preference rank assigned under preference-optimal (blue), revenue-optimal (red), and actual mechanism (dashed black) allocations.

Figure 47. Trade-off in Percentage Gains in Own Tax Revenue Realized Under Preference-Optimal and Revenue-Optimal Allocations.



Notes: This figure plots the percentage gains in own tax revenue realized under preference-optimal (blue), revenue-optimal (red), and actual mechanism (dashed black) allocations.

Figure 48. Preference vs. Performance Trade-off is Affected By Correlation in Preferences.

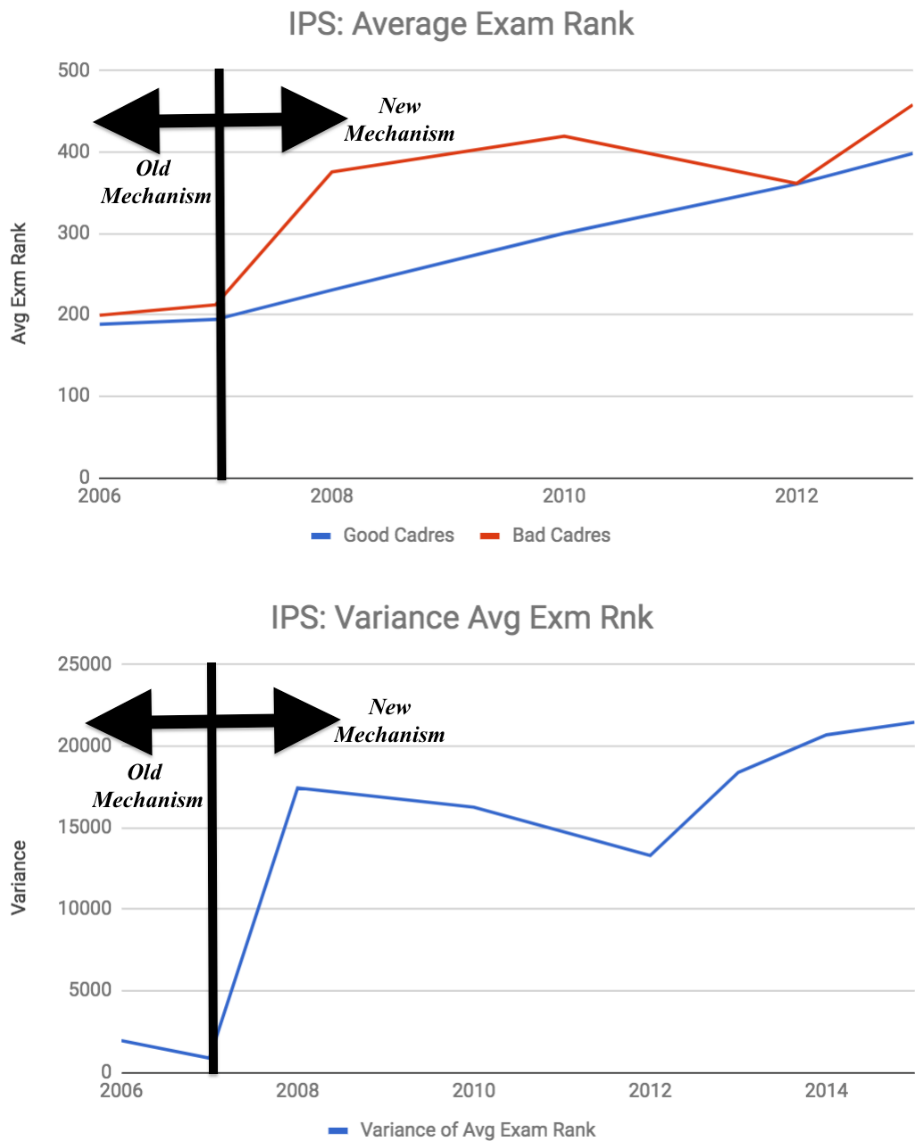


Notes: This figure plots the percentage gains in own tax revenue realized under the Old Mechanism (black), and serial dictatorship in order of exam rank for random preferences (red), preferences minimizing distance from home cadre (purple), and block preferences for good cadres above bad cadres (green).

Appendix A. **Other All-India Services: Police & Forest Services**

This appendix analyzes the analogous effects of the Old and New Mechanisms for the other two All-India Services: the Indian Police Service (IPS) and the Indian Forest Service (IFoS). We make do with considerably incomplete data availability for the IPS and IFoS, however, for years 2008 for IPS and 2015 for IFoS, we have preference rank orders of the candidates, which allows for explicit analysis of correlation in rank order preferences.

Figure 49. Imbalances under New Mechanism for IPS.



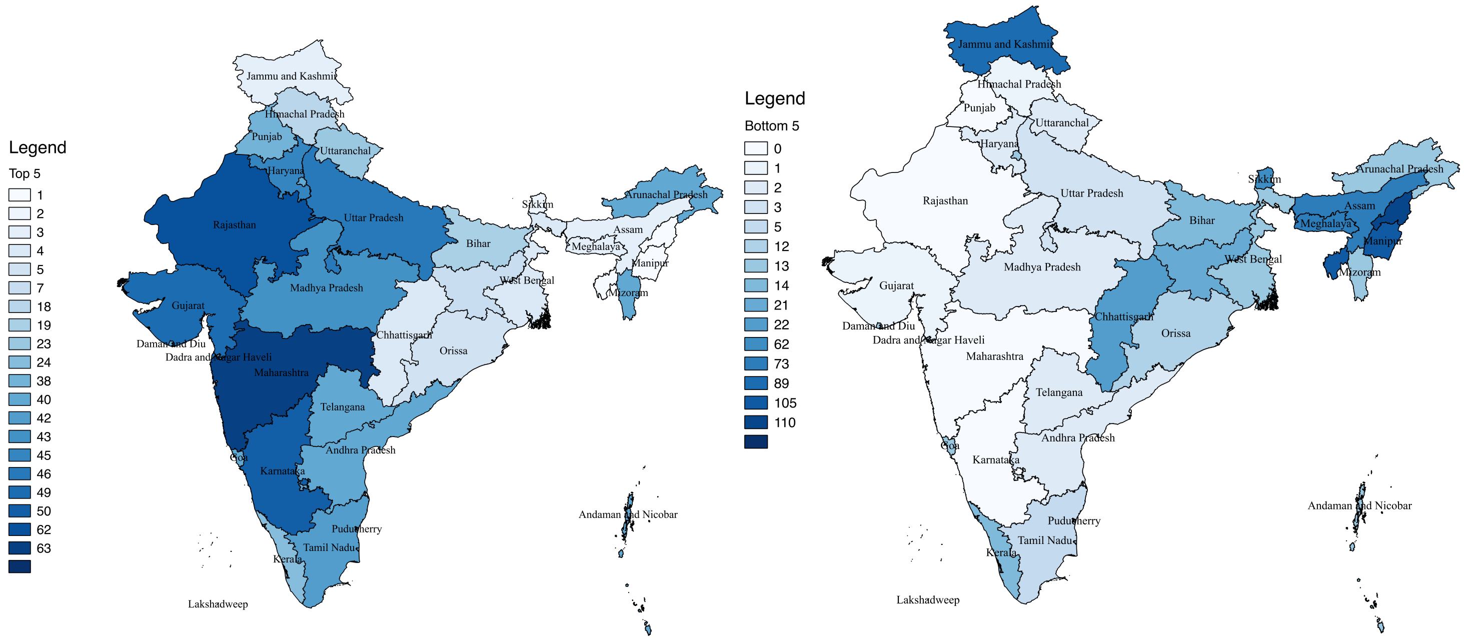
Notes: *Top*: average of with-cadre average exam rank of assigned IPS candidates for good and bad cadres. *Bottom*: variance of within-cadre average exam rank of assigned IPS candidates across all cadres. Notice the divergence in good and bad cadres and a sizable increase in variance in average exam rank across cadres with the New Mechanism. Hence, IPS faces a similar imbalance on the quality dimension as the IAS due to the New Mechanism. *Data available for years 2006-07, 2010, 2012, and 2013-15 from http://mha1.nic.in/ips/ips_misc_cse.htm and year 2008 from http://mha.nic.in/hindi/sites/upload_files/mhahindi/files/pdf/CardAllokts2008.pdf*

Table 17. Preferences of 122 IPS officers admitted from the 2008 Civil Service Examination.

Cadre	Average	Cadre	Std Dev
Rajasthan	5.8	Nagaland	1.5
Maharashtra	6.0	Manipur-Tripura	2.0
Gujarat	6.8	Rajasthan	3.1
Haryana	6.8	Gujarat	3.4
Punjab	7.3	Maharashtra	3.4
Madhya Pradesh	7.3	Sikkim	3.5
Karnataka	7.7	Punjab	3.6
Uttar Pradesh	8.5	Assam Meghalaya	3.7
Uttarakhand	9.8	Orissa	3.9
Andhra Pradesh	9.9	Madhya Pradesh	4.1
Tamil Nadu	10.2	West Bengal	4.2
AGMUT	10.4	Haryana	4.3
Himachal Pradesh	10.6	Uttarakhand	4.3
Bihar	12.7	Himachal Pradesh	4.4
Kerala	12.9	Jammu & Kashmir	4.4
Orissa	14.7	Chhattisgarh	4.5
Jharkhand	15.3	Jharkhand	4.9
West Bengal	15.4	Karnataka	5.1
Chhattisgarh	15.6	Andhra Pradesh	5.7
Sikkim	18.8	Uttar Pradesh	6.0
Assam Meghalaya	19.1	Kerala	6.2
Jammu & Kashmir	20.9	Bihar	6.3
Manipur-Tripura	21.9	AGMUT	6.6
Nagaland	22.9	Tamil Nadu	6.6

Notes: The left column shows the average rank (out of 24 cadres) IPS officers assigned to each cadre, while the right column shows the standard deviation of rank assigned to each cadre. Notice the bad cadres (*bolded*) are consistently ranked at the bottom of IPS officers' rank order preferences. *Data from http://mha.nic.in/hindi/sites/upload_files/mhahindi/files/pdf/CardAllokts2008.pdf*

Figure 50. Top and bottom 5 cadre preferences for IPS 2008 batch.



Notes: The occurrence rate of the cadres among the 5 *most preferred* cadres (*Left*) and the 5 *least preferred* cadres (*Right*) for IPS 2008 batch. Notice that bad cadres are consistently preferred amongst the 5 least preferred cadres and seem to rarely be top preference of IPS officers.

Table 18. Number of Cadres Ranked by IPS 2008 batch.

Fraction of Cadres Ranked	# Officers
24/24	113
21/24	1
18/24	1
17/24	1
12/24	1
11/24	2
10/24	1
5/24	1
0/24	1

Notes: The number of cadres ranked by the 122 IPS officers admitted from the 2008 Civil Service Examination. 93% of IPS officers gave complete preferences (with some indifference). 121 out of 122 indicated wanting to be an insider (i.e., 1st choice was home cadre). Note that no cadre can be deemed unacceptable, so incomplete preferences are treated as the candidate being indifferent over all unranked cadres. *Data from http://mha.nic.in/hindi/sites/upload_files/mhahindi/files/pdf/CardAllokts2008.pdf*

Table 19. Preferences of 110 IFoS officers admitted from the 2015 and 2016 Civil Service Examinations.

Cadre	Average	Cadre	Std Dev
Madhya Pradesh	4.9	Nagaland	3.0
Maharashtra	6.3	Maharashtra	3.3
Karnataka	7.3	Manipur	3.4
Rajasthan	7.5	Tripura	3.6
Gujarat	7.7	Gujarat	3.8
Himachal Pradesh	9.0	Madhya Pradesh	3.9
Uttarakhand	9.4	West Bengal	4.3
Uttar Pradesh	9.7	Jammu Kashmir	4.5
Andra Pradesh	10.3	Assam Meghalaya	4.7
Telangana	11.4	Himachal Pradesh	5.0
Haryana	12.3	Karnataka	5.1
AGMUT	12.3	Orissa	5.1
Tamil Nadu	12.9	Rajasthan	5.3
Punjab	12.9	Sikkim	5.3
Kerala	12.9	Punjab	5.6
Chhattisgarh	13.7	Jharkhand	5.7
Orissa	14.4	Andra Pradesh	6.0
Jharkhand	14.9	Kerala	6.1
Bihar	15.2	AGMUT	6.1
West Bengal	17.2	Bihar	6.2
Sikkim	17.8	Chhattisgarh	6.2
Assam Meghalaya	18.7	Uttar Pradesh	6.3
Jammu & Kashmir	21.8	Uttarakhand	6.3
Tripura	22.7	Telangana	6.5
Manipur	23.2	Haryana	6.5
Nagaland	24.3	Tamil Nadu	7.1

Notes: The left column shows the average rank (out of 26 cadres) IFoS officers assigned to each cadre, while the right column shows the standard deviation of rank assigned to each cadre. Notice the bad cadres (*bolded*) are consistently ranked at the bottom of IFoS officers' rank order preferences. *Data from http://ifs.nic.in*

Appendix B. **What Civil Service Exam Rank Captures.**

Since exam rank is the only standardized measure of quality available for the government at the time of cadre allocation and because the government seeks an equitable balance of quality across cadres, it is important to understand what these exam ranks are capturing and what drives the variation in exam scores/ranks. Appendix G lays out the composition of the Civil Service Examination. The data we have on individual scores is from pre-2012 when the papers were out of 2300 points consisting of Essay (200 pts), General Studies I (300 pts) and II (300 pts), Optional Ii (300 pts) and Iii (300 pts), Optional IIi (300 pts) and IIii (300 pts), and Interview (300 pts). In this appendix, we analyze which exams explain the variation in exam scores and on what dimensions exam rank sorts individuals.

From a principal component analysis in Table 20, we see that the first principal component which is mostly the 300-point Interview explains 28% of the total variance in the exam data. And the second principal component which explains another 16% of the variance, comprises of the General Studies exams, which focus on Indian economics, politics, history, institutions, etc. Hence, communication skills and India-specific knowledge explains around 44% of exam score variation.

Along similar lines, in Table 21 we provide the correlation matrix of the various exams comprising the cumulative Civil Service Examination score. Similar to the principal component analysis, we see that the Interview/Personality test, Optional Ii, and General Studies I and II exams are most highly correlated with the cumulative score.

Both of these exercises suggest that India-specific knowledge of "Indian heritage, culture, history, geography of the world and society, governance, constitution, polity, social justice, and international relations" tested in the General Studies papers, along with communication, presentation, and leadership skills tested in the Interview/Personality test are the primary exams which sort the cumulative exam scores and exam ranks. And it is not proficiency in the specialized, optional subject tests which sort exam ranks and explain substantial variation in exam scores.

Table 20. Principal Component Analysis of Civil Service Examination Scores.

	Comp1	Comp2	Comp3	Comp4	Comp5	Comp6	Comp7	Comp8
Essay(200pts)	-0.02	0.05	-0.12	-0.25	-0.14	-0.18	-0.52	0.77
GenStudiesI(300pts)	-0.05	0.82	0.03	0.04	0.41	-0.32	0.19	0.09
GenStudiesII(300pts)	0.03	0.39	0.01	0.28	-0.39	0.72	0.16	0.27
OptionalIi(300pts)	-0.11	-0.05	0.65	0.63	-0.18	-0.30	-0.19	0.07
OptionalIii(300pts)	-0.17	-0.16	0.64	-0.41	0.41	0.33	0.17	0.24
OptionalIIi(300pts)	-0.04	-0.27	-0.33	0.54	0.64	0.20	-0.05	0.27
OptionalIIii(300pts)	-0.10	-0.25	-0.11	0.04	-0.22	-0.32	0.77	0.41
Interview(300pts)	0.97	-0.04	0.17	0.01	0.09	-0.05	0.05	0.12
%age variance	27.68	15.78	12.54	10.90	9.39	8.92	7.81	6.97

Notes: Principal Component Analysis of the 2005 Civil Service Exam Scores of the 457 individuals who qualified from the Main examination. The first 8 principal components are shown along with the percentage of variance explained by each principal component. Notice that around 44% of variance is explained by the first two principal components predominantly weighting the Interview (1st principal component) and General Studies exams (2nd principal component).

Table 21. Correlation of individual exams constituting the Civil Service Examination with the total score.

	ess	gsI	gsII	optIi_300	optIii	optIIi	optIIii	Intrvw	Total
ess	1								
gsi	0.0217	1							
gsii	-0.0357	0.1736	1						
optIi	-0.0808	-0.0064	0.0177	1					
optIii	-0.0371	-0.0539	-0.0897	0.1232	1				
optIIi	-0.0761	-0.1183	-0.0707	-0.0007	-0.0702	1			
optIIii	-0.0207	-0.1483	-0.1115	0.0217	-0.0073	0.0517	1		
Intrvw	-0.0477	-0.0629	0.0261	-0.0960	-0.1622	-0.0537	-0.1329	1	
Total	0.2100	0.3483	0.3582	0.3738	0.2503	0.2354	0.1776	0.4057	1

Notes: Correlation matrix for the 8 exams comprising the 2005 Civil Service Examination along with the cumulative score for the 457 individuals who qualified from the Main examination. The exams are Essay (200 pts),General Studies I (300 pts) and II (300 pts), Optional Ii (300 pts) and Iii (300 pts), Optional IIi (300 pts) and IIii (300 pts), and Interview (300 pts), and cumulative score (2300 points). Interview, General Studies I and II, and Optional Ii exams are most correlated with the cumulative score.

Appendix C. Supply-side effects of the change in mechanism

In this appendix we analyze whether the change in mechanism affected the pool of applicants appearing for the Civil Service Examination and/or the pool of selected candidates. The change in cadre allocation mechanisms in 2008 was not the only change to potentially affect the supply of civil servant aspirants, hence this section provides only suggestive evidence using the 2008 mechanism change. We find that there were no discrete jumps and mostly only a continuation of long-run trends in observables from the pre-2008 to post-2008 pools of applicants and/or selected civil servants.

Although we lack the empirical variation for precisely estimating the causal effects of the change in mechanism on observable characteristics, our suggestive evidence suggests that while the number of applicants per post (Figure 51) has increased since the change in mechanism, education levels (Figure 52), age at entry (Figure 53), and gender composition (Figure 54) seem not to have undergone any major shifts. In fact, if anything, representation of women is on a slow upward trend, age of entry is relatively flat, and the highest attained education qualifications seem to have declined in the post-2008 mechanism regime.

Whether the All-India services have maintained their prestige in the new industrial and labor environment in India, whether government salaries are still competitive with those in the private sector, and whether these civil services still attract the best and brightest aspirants are all widely debated issues in recent times. The change to the 2008 mechanism which incorporates candidates' preferences over where they want to serve, may be rationalized as an attempt to attract the best and brightest applicants in the country and compete with enticing outside options such as finance, consulting, and technology jobs which have been on the rise in India. However, we do not find substantial evidence suggesting that the applicant pool and/or the pool of selected candidates has witnessed any significant structural shifts post-2008.

Figure 51. Number of Applicants per Post taking the Civil Service Examination (Main).

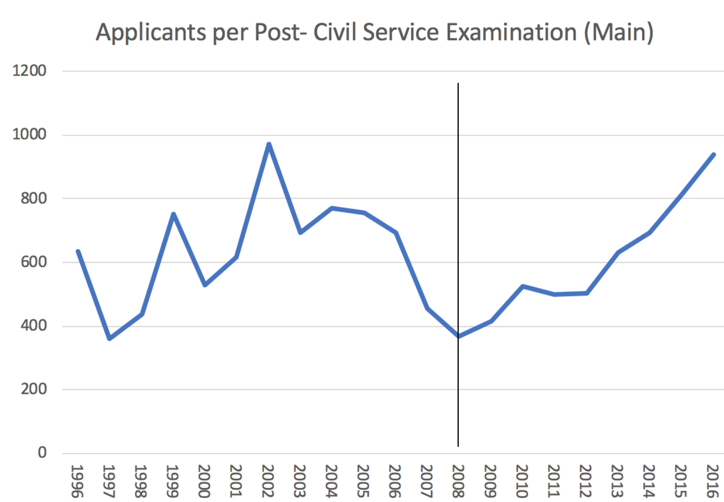
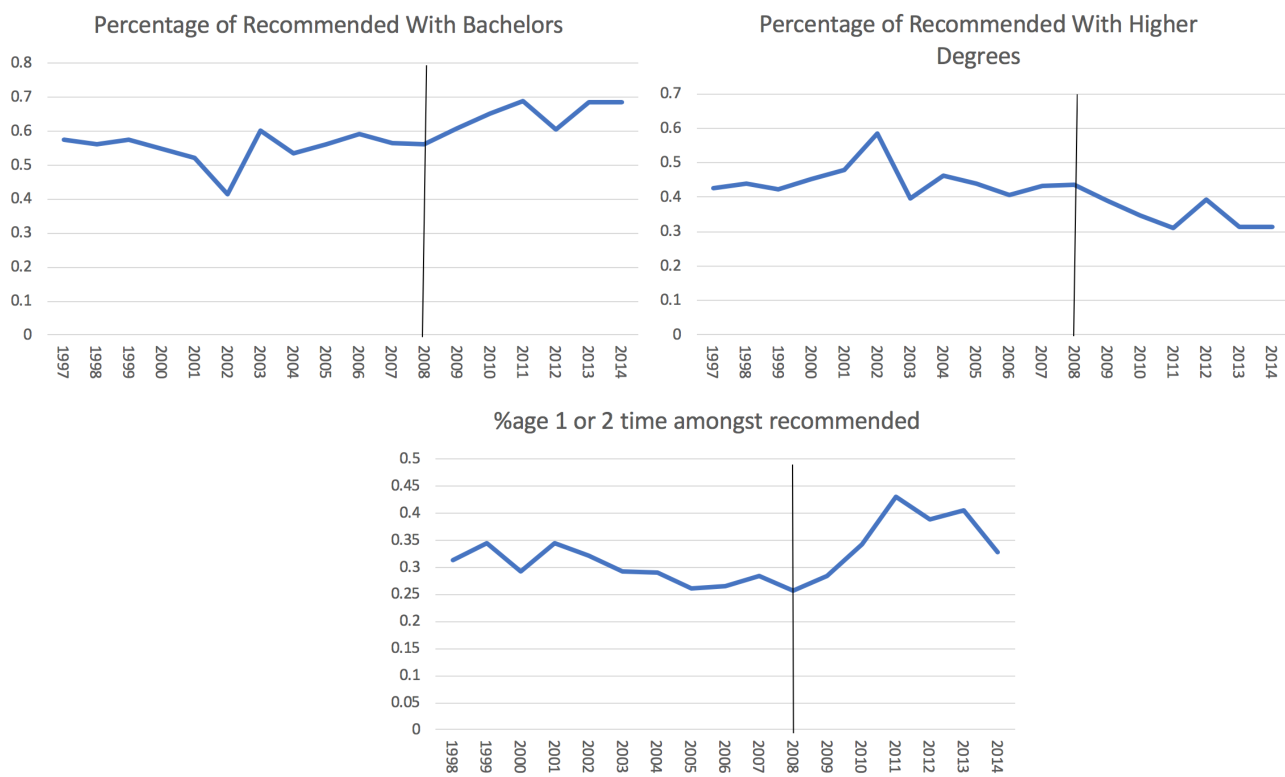
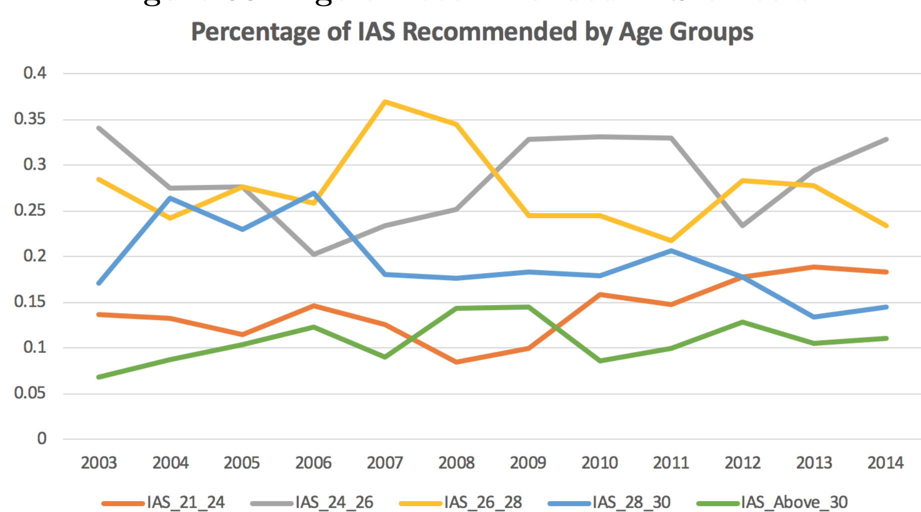


Figure 52. Education & exam attempts distribution in recommended IAS officers.



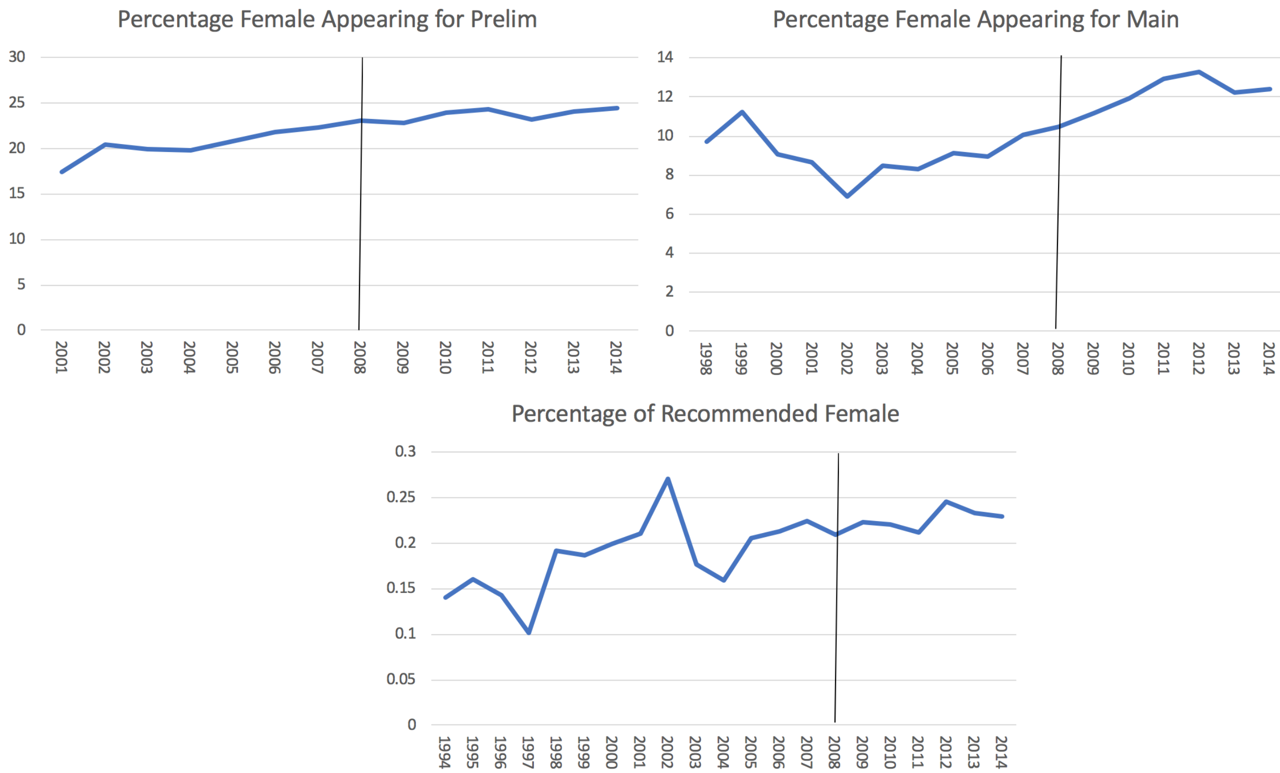
Notes: *Top Left*: percentage of recommended IAS candidates with Bachelors degree. *Top Right*: percentage of recommended IAS candidates with Higher degrees *Bottom*: percentage of recommended IAS candidates taking the Civil Service Examination for the 1st or 2nd time.

Figure 53. Age of recommended IAS officers.



Notes: Age distribution of recommended IAS officers across categories 21-24, 24-26, 26-28, 28-30, and above 30.

Figure 54. Gender balance in CSE and IAS.



Notes: *Top Left*: percentage of females amongst those appearing for Preliminary Civil Service Examination. *Top Right*: percentage of females amongst those appearing for the Main Civil Service Examination. *Bottom*: percentage of females amongst candidates recommended for IAS.

Appendix D. Measuring Correlation Across Individuals' Preferences.

We define a novel measure of correlation across preference rank orders, which is a generalization of the Spearman rank correlation coefficient to N rank-ordered lists. When considering the ranking of $n = 1, ..., N$ candidates over $c = 1, ..., C$ cadres, we suggest the following correlation measure

$$\rho = 1 - \frac{\sum_{c=1}^{C}\left(\frac{1}{N-1}\sum_{n=1}^{N}(r_{nc} - \overline{r}_c)^2\right)}{C\left(\frac{(C-1+1)^2-1}{12}\right)} \tag{1}$$

Measuring how much variance there is in ranking for each alternative across candidates relative to its average ranking, and summing these measures across all of the ranked alternatives, gives us a measure of how much variation there is in the candidates' ranking of the alternatives (i.e., numerator). This quantity is then bench-marked against the variance of a discrete random distribution (i.e., denominator).

This general measure has some nice properties:

- If all candidates rank their rank order preferences identically, the numerator of the second term is 0, and hence $\rho = 1$ (i.e., perfect positive correlation).
- If all candidates randomize their rank order preferences, the parenthesis term in the numerator of the second term becomes the variance of a discrete uniform distribution for integers $\{1, ..., C\}$, which approaches $\frac{(C-1+1)^2-1}{12}$ for large N, hence the second term goes to 1 and thus $\rho \to 0$ (i.e., no correlation).
- This measure is an equally weighted average of Spearman rank correlation coefficients for all distinct pairs of individuals.

  Proof: Starting from average of Spearman rank correlation coefficients for all N choose 2 pairs $i \neq j$ of candidates, we show that this coincides with our measure

$$\begin{aligned}
\frac{1}{\frac{N!}{2!(N-2)!}}\sum_{i\neq j\in N}\left(1 - \frac{6\sum_{c=1}^{C}(r_{ic} - r_{jc})^2}{C(C^2-1)}\right) &= 1 - \frac{1}{N}\sum_{i=1}^{N}\sum_{j=1}^{N}\left(\frac{\frac{1}{N-1}\sum_{c=1}^{C}(r_{ic} - r_{jc})^2}{\left(\frac{C(C^2-1}{12}\right)}\right) \\
&= 1 - \left(\frac{\sum_{c=1}^{C}\frac{1}{N-1}\sum_{i=1}^{N}(r_{ic} - \frac{1}{N}\sum_{j=1}^{N} r_{jc})^2}{\left(\frac{C(C^2-1}{12}\right)}\right) \\
&= 1 - \frac{\sum_{c=1}^{C}\left(\frac{1}{N-1}\sum_{i=1}^{N}(r_{ic} - \overline{r}_c)^2\right)}{C\left(\frac{(C-1+1)^2-1}{12}\right)} = \rho
\end{aligned}$$

Table 22. Correlation across individuals' rank order preferences for IPS 2008, IFS 2015, and IFS 2016.

	IPS 2008	IFS 2015	IFS 2016
Number of Civil Servants	122	110	110
Number of Cadres	24	26	26
Correlation in Pref	.5261	.4845	.5211
Correlation in Pref (only complete pref)	.5704	.4845	.5211

Appendix E. **Nested Matching Mechanisms.**

While this paper primarily focuses on the matching mechanism used to assign IAS officers to state cadres, it is important to realize that this matching mechanism is nested inside another matching mechanism to allocate the exact service within the many civil services which take the Civil Services Examination.

The entire process is as follows: i) candidates take the Preliminary examination, ii) those who qualify to appear for the Main examination and report their service preferences,[55] iii) those who are selected from the Main examination are assigned to a service via the **Service Allocation Mechanism**, and finally, iv) each service then conducts its relevant training and within-service allocation.[56] Note that unlike in the Police and Administrative Services, other civil services do not necessarily have life-long assignments to cadres, and moreover, IFS assignments are often postings to foreign countries.

The Service Allocation mechanism is simply a serial dictatorship in order of exam rank. However, it is important to note that despite serial dictatorship being strategyproof mechanism by itself, since the Service Allocation Mechanism is followed by the within-service allocation— such as the cadre allocations for the IPS and IAS—where relative rank matters, this system is *not strategyproof*.

By backwards induction, even if the cadre allocation system were strategyproof, if it prioritizes in order of relative exam rank amongst those who are allotted to say the IAS, the service allocation mechanism is rendered to be non-strategyproof. For example, the strategizing involves figuring out what one's relative rank would be after qualifying past the Main examination, how exam toppers above you (if any) above you chose their services, and hence, what your relative ranking would be for each of the different services. Relative ranking in the service would yield a lottery over within-service assignment and hence a lottery over utilities for each post. If within-service allocations prioritize by exam rank, such as in the New Mechanism under IAS and IPS cadre allocation mechanisms, then, expected value from $v_s(i) \geq v_s(i+1)$ for any relative rank i within the service. Namely, within a service s, a higher rank provides weakly higher expected payoff. Note, that under the Old Mechanism which only prioritized exam rank for the insider category, but not for outsider positions, the inequality does not necessarily hold. For example, being 10th versus 11th might get you

[55]The services which come under the common Civil Service Examination are i. Indian Administrative Service (IAS), ii. Indian Foreign Service, iii. Indian Police Service, iv. Indian P&T Accounts & Finance Service, Group 'A', v. Indian Audit & Accounts Service, Group 'A', vi. Indian Customs & Central Excise Service, Group 'A', vii. Indian Defence Accounts Service, Group 'A', viii. Indian Revenue Service, Group 'A', ix. Indian Ordnance Factories Service, Group 'A', x. Indian Postal Service, Group 'A', xi. Indian Civil Accounts Service, Group 'A', xii. Indian Railway Traffic Service, Group 'A', xiii. Indian Railway Accounts Service, Group 'A', xiv. Indian Railway Personnel Service, Group 'A', xv. Posts of Assistant Security Commissioner in Railway Protection Force, Group 'A', xvi. Indian Defence Estates Service, Group 'A', xvii. Indian Information Service, (Junior Grade), Group 'A', xviii. Indian Trade Service, Group 'A', xix. Indian Corporate Law Service, Group 'A', xx. Armed Forces Headquarters Civil Service, Group 'B', xxi. Delhi, Andaman & Nicobar Islands, Lakshadweep, D D & NH Civil Service, Group 'B', xxii. Delhi, Andaman & Nicobar Islands, Lakshadweep, D D & NH Police Service, Group 'B', xxiii. Pondicherry Civil Service, Group 'B', xxiv. Pondicherry Police Service, Group 'B

[56]Both service and cadre preference rank orders are given before the Main examination, after which the examination and interview are held. Thus, candidates do not know their ranks while ranking their preferences. The total number of vacancies and service-wise breakdown are announced in the advertisement, but the number of vacancies in each state cadre is not known.

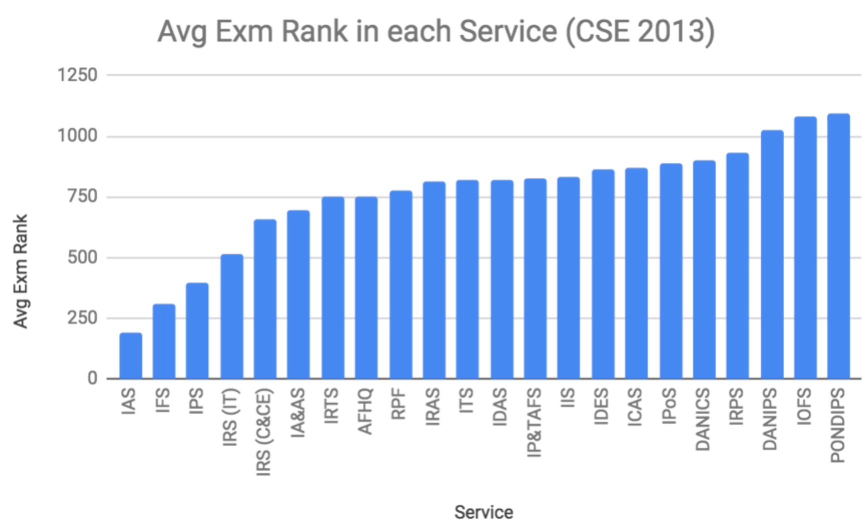
allocated to different cadres as an outsider, and the candidate may prefer allocation when he's 11th than when he's 10th within the IAS.

With the New Mechanism however, both in the IAS and the IPS, candidates would be weakly better off having a better rank within the service.

In the data, we see that most exam toppers opt for the IAS, followed by IFS and IPS, and then followed by a mix of the other civil services. Figure 55 shows that the lowest average exam rank services—most competitive and most sought-after—are 1) IAS, 2) IPS, 3) IFS, 4) IRS, and then the rest of the services taking the Civil Service Examination. It is possible that preferences of the exam toppers are such that they prefer every IAS cadre allocation to any IPS, IFS or other service position. However, suppose they vastly prefer being in their home cadre relative to any other assignment, then it is possible that a candidate who otherwise prefers IAS over IPS, would rank IPS higher in the service preference, if there is a better chance he gets an insider position in the IPS, but not in the IAS.

However, we note that it is particularly difficult in this instance to strategize since the service preference is chosen before the candidate knows his final rank, and hence, it requires a lot of information to effectively strategize.

Figure 55. Average exam rank in the Civil Service Examination for year 2013 across the various services.



Appendix F. Qualitative Description of other Market Design Considerations

In this appendix, we qualitatively describe four important considerations which are innately related to cadre allocation: i) marriage between civil servants, ii) inter-cadre deputation, iii) state civil service promotion, and iv) lateral entry. Without taking any normative or positive stance, we simply wish to describe the policies at hand, emphasize how they shape incentives, and provide references to related market design solutions used in other applications where possible. All of these issues were highlighted in interviews and conversations with various IAS officers.

F.1. Marriage amongst Civil Servants.

The only way an All-India Services officer can get a permanent change in their cadre allocation which we describe in this paper, is through marriage with another civil servant assigned to another state cadre. This is becoming an increasingly important concern over the years as marriages amongst All-India Services appear to be more frequent over the years.[57] Rules dictating possible cadre changes as a result of two All-India Services officers getting married have changed over the years[58] and requests are dealt with on a case-by-case basis by the Department of Personnel and Training.

Currently, there are a few considerations taken into account in this process. First, the couple has four choices: i) choose cadre of spouse 1, ii) choose cadre of spouse 2, iii) choose to jointly move to a 3rd cadre which neither spouse is originally assigned to, or iv) remain in two separate cadres. In granting a move to a cadre where a spouse has been originally assigned to, the government considers whether this cadre is under- or over-prescribed relative to its need and strength. For example, moves to under-prescribed or deficient cadres are given priority. Moreover, if a spouse's cadre is one's home cadre, a move to that cadre is not allowed due to insider constraint considerations. Finally, some IAS officers choose to remain in two separate cadres and take on temporary deputations to each other's cadres or contemporaneously to a common third cadre. Which of the four options a couple opts for depends on what the Department of Personnel and Training approves, what the available moves are, and other career considerations of each spouse.

Although this topic in the Indian context relates to ex post (after initial assignment) switches due to marriage, the problem of married couples entering the initial matching mechanism has been addressed in many mechanisms around the world, for example, the National Resident Matching Program:

Some references:

- Kojima, Fuhito, Parag A. Pathak, and Alvin E. Roth. "Matching with couples: Stability and incentives in large markets." The Quarterly Journal of Economics 128.4 (2013): 1585-1632.
- Roth, Alvin E. "The evolution of the labor market for medical interns and residents: a case study in game theory." Journal of Political Economy 92.6 (1984): 991-1016.

[57]See https://economictimes.indiatimes.com/news/politics-and-nation/33-ias-officers-seek-cadre-change-many-due-to-marriage/articleshow/47150661.cms for 2015 requests for cadre changes on basis of marriage.
[58]See https://www.hindustantimes.com/india-news/pm-changes-rules-to-help-married-ias-ips-officers-work-at-one-place/story-SpzB04bWKvuNbXw6bJWWyJ.html for the most recent change in policy.

• Roth, Alvin E., and Elliott Peranson. "The redesign of the matching market for American physicians: Some engineering aspects of economic design." American economic review 89.4 (1999): 748-780.

F.2. **Inter-cadre Deputation.**
Other than marriage considerations as explained above, the cadre allocation is permanent. However, IAS officers can be deputed temporarily to another cadre or to the Centre. Inter cadre deputation is important to understand incentives; IAS officers believe that those in bad cadres are more likely to petition for temporary inter-cadre deputation to another cadre. Moreover, some All-India Services couples choose to remain in separate cadres after marriage, and seek temporary deputations to the spouse's cadre or jointly to a different cadre. Petitions need to be made for inter-cadre deputation, the central government and both state governments must agree, and rules establish minimum requirements of tenure (usually 9 years in assigned cadre) before being qualified to request inter-cadre deputation, maximum tenure on an inter-cadre deputation (3 years, increased to 5 years from 2016[59]), and a life-long limit of 5 inter-cadre deputations over the course of a career for All-India Services. For cadres where there is a shortage of All-India Service officers—Chhattisgarh, Sikkim, Nagaland, Uttarakhand, and Manipur-Tripura—9 year tenure requirements are relaxed to 3 year tenure requirements in the assigned cadre.

Reference for complete set of rules for inter-cadre deputation:

• Department of Personnel and Training Circular:
  http://documents.doptcirculars.nic.in/D2/D02ser/13017_16_2003-AIS-I-D-08112004.pdf

F.3. **State Civil Service Promotion.**
While we focus in this paper on the cadre allocation policies for direct recruits qualifying from the Civil Service Examination, another method of entry into the All-India Services includes appointment by promotion from state civil services. Before 2013, promotion of state civil servants used to be based on seniority and performance evaluation based on annual confidential reports; however, from 2013 onwards state civil service promotees have to take the UPSC exam and qualify.[60]

There are a few considerations in this process worth noting. First, state service promotees had different (often times easier) entry exams and less competition compared to IAS officers. Second, state service promotees do not enter the Old or New Mechanism, but get promoted as insiders to their home cadre. Third, in the past, cadres where many state promotees were promoted to insider IAS, posted fewer insider vacancies in the Cadre Allocation process we analyze in this paper, since insider balance was crowded out by state promotees. Fourth, for seniority calculations, for every 2.5 years a state civil servant serves, he is awarded 1 year of IAS seniority when promoted.

State Civil Service promotion thus becomes an alternative path to enter the All-India Services with less competition at start for qualifying for the service through exams and interviews, guarantee of home cadre if get promoted, and seniority adjustment of 1 year/2.5 years. Finally, promotion to All-India Services requires the approval of a minister, and hence, concerns of favoritism have also been raised.

[59]See https://economictimes.indiatimes.com/news/politics-and-nation/centre-increases-inter-cadre-deputation-period-up-to-five-years/articleshow/51882169.cms

[60]See https://timesofindia.indiatimes.com/india/Exams-for-state-civil-services-officers-for-promotion-to-IAS/articleshow/27861653.cms

References:

- See UPSC rules and regulations for appointment by promotion:
  http://www.upsc.gov.in/about-us/divisions/all-india-services-ais-branch/appendices/ias-appointment-promotion-regulations-1955

F.4. **Lateral Entry.**

Whether or not to allow lateral entry into the elite civil services has been a hotly debated topic over the years. Regardless of the formal rules, appointees have made it to high, senior positions in government without having to climb the Civil Service hierarchy. At the heart of the debate, is the question of specialist versus generalist: whether certain administrative and policy-making jobs require specialist knowledge within the particular domain or whether a generalist can manage just as well. The All-India Services, which evolved from the colonial Indian Civil Services, has maintained confidence in a generalist system, but lateral entry allows for specialists to be recruited laterally into the system as needed. The further question remains: after a lateral appointment to a post in the government bureaucracy, can these folks continue in the civil services? If so, in which cadre and at what seniority in the bureaucratic hierarchy?

Appendix G. Civil Service Examination & Interview Format

In the mandarin system of Indian civil service where selection into the bureaucracy is based on candidates' performance on the Civil Service Examination, the exam rank/score represents the only standardized proxy for quality the government has at the time of assignment. Exam rank plays a key role in the assignment processes and the government's desire to implement a quality balance constraint as highlighted in this paper, making the Civil Service Examination an integral part of the selection/matching process. This section replicates selected sections from UPSC's 2017 Examination Notice.[61] The syllabus and precise weighting changes slightly across years in our sample,[62] but this provides an overall idea of the examination format and syllabus so that we better understand the screening process.

Appendix I, Section I: Plan of Examination (p. 124).
"The competitive examination comprises two successive stages:

(1) Civil Services (Preliminary) Examination (Objective type) for selection of candidates for Main Examination; and
(2) Civil Services (Main) Examination (Written and Interview) for selection of candidates for various Services and posts.

The Preliminary Examination will consist of two papers of Objective type (multiple choice questions) and carry a maximum of 400 marks... This examination is meant to serve as a screening test only; the marks obtained in the Preliminary Examination by the candidates who are declared qualified or admission to the Main Examination will not be counted for determining their final order of merit. The number of candidates to be admitted to the Main Examination will be about twelve to thirteen times the total approximate number of vacancies to be filled in the year through this examination."

Appendix I, Section II: Scheme and subjects for the Preliminary and Main Examination (p. 125).
"**A) Preliminary Examination:**

Examination shall comprise of two compulsory Papers of 200 marks each.

- Paper I General Studies:
  - "i) Current events of national and international importance, ii) history of India and Indian National Movement, iii) Indian and World Geography-Physical, Social, Economic, Geography of India and the World, iv) Indian Polity and Governance- Constitution, Political System, Panchayati Raj, Public Policy, Right Issues, etc, v) Economic and Social Development- Sustainable Development, Poverty, Inclusion, Demographics, Social Sector Initiatives, etc, vi) General issues on Environmental ecology, Bio-diversity and climate change - that do not require subject specialization, vii) General Science" (p. 128)
- Paper II General Studies:

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[61] This official notice provides a more detailed syllabus:
http://www.upsc.gov.in/sites/default/files/Engl_CSP_2017.pdf

[62] The largest change in exam format was across pre-2012 exams (2300 points consisting of Essay (200 pts), General Studies I (300) and II (300), Optional Ii (300) and Iii (300), Optional IIi(300) and IIii(300), and Interview (300), and post-2012 (2025 points) system outlined in the text.

- "Comprehension, Interpersonal skills including communication skills, local reasoning and analytical ability, decision making and problem solving, general mental ability, basic numeracy (Class X level)" (p. 128)
- The General Studies Paper-II of the Civil Services (Preliminary) Examination will be a qualifying paper with minimum qualifying marks fixed at 33%.

B) Main Examination:

The written examination will consist of the following papers:

Qualifying Papers:

- Paper-A: One of the Indian Language to be selected by the candidate (300 marks)
  - Language must be chosen from Assamese, Bengali, Gujarati, Hindi, Kannada, Kashmiri, Konkani, Malayalam, Manipuri, Marathi, Nepali, Oriya, Punjabi, Sanskrit, Sindhi, Tamil, Telugu, Urdu, Bodo, Dogri, Maithilli, and Santhali (p. 126).
- Paper-B: English (300 marks)

Papers to be counted for merit:

- Paper-I: Essay (250 Marks)
- Paper-II General Studies-I: Indian Heritage and Culture, History and Geography of the World and Society (250 marks)
- Paper III General Studies-II: Governance, Constitution, Polity, Social Justice and International Relations (250 marks)
- Paper IV General Studies-III: Technology, Economic Development, Bio-diversity, Environment, Security and Disaster Management (250 marks)
- Paper V General Studies-IV: Ethics, Integrity and Aptitude (250 marks)
- Paper VI Optional Subject - Paper 1 (250 marks)
- Paper VII Optional Subject - Paper 2 (250 marks)
  - The list of optional subjects for Main Examinations: Agriculture, Animal Husbandry and Veterinary Science, Anthropology, Botany, Chemistry, Civil Engineering, Commerce and Accountancy, Economics, Electrical Engineering, Geography, Geology, History, Law, Management, Mathematics, Mechanical Engineering, Medical Science, Philosophy, Physics, Political Science and International Relations, Psychology, Public Administration, Sociology, Statistics, Zoology, Literature of any one of Indian languages (p. 126)

Sub Total: Written test (1750 marks)
Personality Test (275 marks)

"The candidate will be interviewed by a Board who will have before them a record of his career. He will be asked question on matters of general interest. The object of the interview is to assess the personal suitability of the candidate for a career in public service by a Board of competent and unbiased observers. The test is intended to judge the mental caliber of a candidate. In broad terms this is really an assessment of not only his intellectual qualities but also social traits and his interest in current affairs. Some of the qualities to be judged are mental alertness, critical powers of assimilation, clear and logical exposition, balance of judgment, variety and depth of interest, ability for social cohesion and leadership and moral integrity." (p. 127)

Grand Total: 2025 marks"

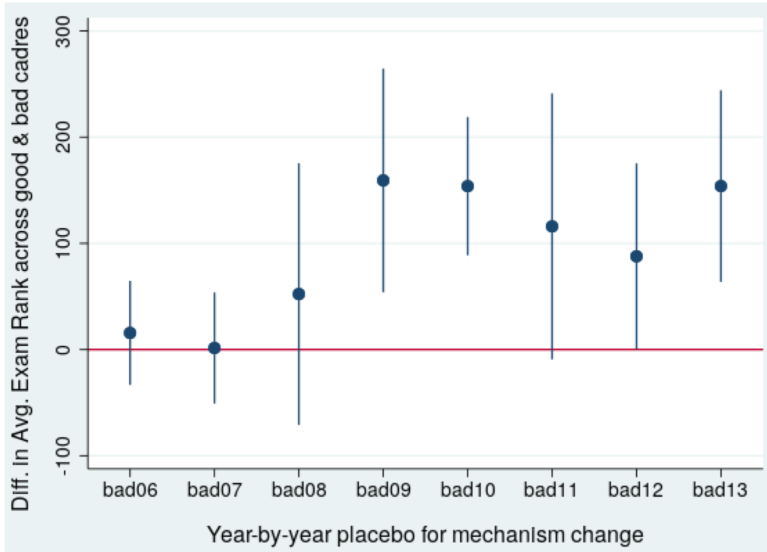
Table 23. Effect of Mechanism on Exam Rank by State: Year-by-year Effects & Placebo tests

	(1) Avg ExmRnk	(2) Avg ExmRnk	(3) Avg ExmRnk	(4) Normalized ExmRnk	(5) Normalized ExmRnk	(6) Normalized ExmRnk
Badcadre×NewMech	114.8***			0.784***		
	(23.14)			(0.190)		
bad08		46.58	52.27		0.396	0.456
		(55.97)	(59.14)		(0.476)	(0.514)
bad09		153.6***	159.2***		1.136***	1.196***
		(46.12)	(50.56)		(0.360)	(0.413)
bad10		148.1***	153.8***		0.995***	1.056***
		(28.96)	(31.23)		(0.190)	(0.232)
bad11		110.3**	115.9*		0.862*	0.923*
		(52.73)	(60.10)		(0.417)	(0.498)
bad12		82.10*	87.79**		0.475*	0.536*
		(43.33)	(42.00)		(0.255)	(0.262)
bad13		148.2***	153.9***		0.838***	0.899***
		(41.71)	(43.33)		(0.222)	(0.260)
bad07			1.425			0.0163
			(25.14)			(0.266)
bad06			15.64			0.166
			(23.53)			(0.249)
Constant	78.60***	78.60***	78.60***	-0.115	-0.115	-0.115
	(9.207)	(9.321)	(9.351)	(0.0895)	(0.0906)	(0.0908)
Year FE	✓	✓	✓	✓	✓	✓
State FE	✓	✓	✓	✓	✓	✓
Observations	216	216	216	216	216	216

Notes: This table expands upon the difference-in-difference specifications for state average exam ranks (col 1-3) and normalized state exam ranks (col 4-6) from Table 2, using data from 2005-13. The overall effect (col 1 and 4) is split apart into year-by-year effects (col 2 and 5) and then placebo tests by including 2006 and 2007 as post-treatment years (col 3 and 6). As expected, the placebo tests have insignificant effects on these Old Mechanisms years. See Figure 56 for graph of placebo tests. Standard errors in parentheses are clustered at the state cadre level

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure 56. Placebo Test: Year-by-year placebo tests for change of mechanism on detrended own tax revenue.



Notes: This figure plots the year-by-year placebo tests for change of mechanism on difference in average exam ranks across good and bad cadre, from Table 23. We see that under the Old Mechanism years (2006-07), the estimates are small and near zero; whereas, under the New Mechanism years (2008-2013), the difference between good and bad cadres' average exam rank is large and positive.

Table 24. Non-Tax Revenue Robustness (incl. and excl. Maharashtra & Haryana)

	excl. Maharashtra and Haryana		excl. Maharashtra		excl. Haryana	
	(1)	(2)	(3)	(4)	(5)	(6)
	DetNonTax	NonTax	DetNonTax	NonTax	DetNonTax	NonTax
Badcadre×NewMech	-349.2	-70.81	-1006.0	-96.42	-633.0	-342.6
	(366.0)	(214.9)	(751.8)	(205.4)	(455.8)	(354.2)
Badcadre×NewMech×lineartrend		-34.80		-113.7		-36.30
		(55.34)		(99.57)		(53.27)
lineartrend		622.2***		604.3***		610.9***
		(8.89)		(20.84)		(14.75)
Constant	1127.5***	868.0***	1136.6***	784.7***	1198.9***	891.6***
	(99.58)	(53.04)	(240.9)	(108.7)	(134.2)	(62.7)
Year FE	✓	✓	✓	✓	✓	✓
State FE	✓	✓	✓	✓	✓	✓
State Linear Time Trend		✓		✓		✓
Observations	260	260	270	270	270	270

Notes: Since Haryana and Maharashtra cause the supposed jump in the non-tax revenues (see Figures 21 and 23), we present robustness results by replicating analysis from Tables 9 and 11, but excluding Haryana and Maharashtra individually, and both together. Regardless of whether these two states are included or not, the placebo variable (non-tax revenues) never shows any significant effect of the New Mechanism for either specification: detrended difference-in-difference or structural break. Standard errors in parentheses are clustered at the state cadre level

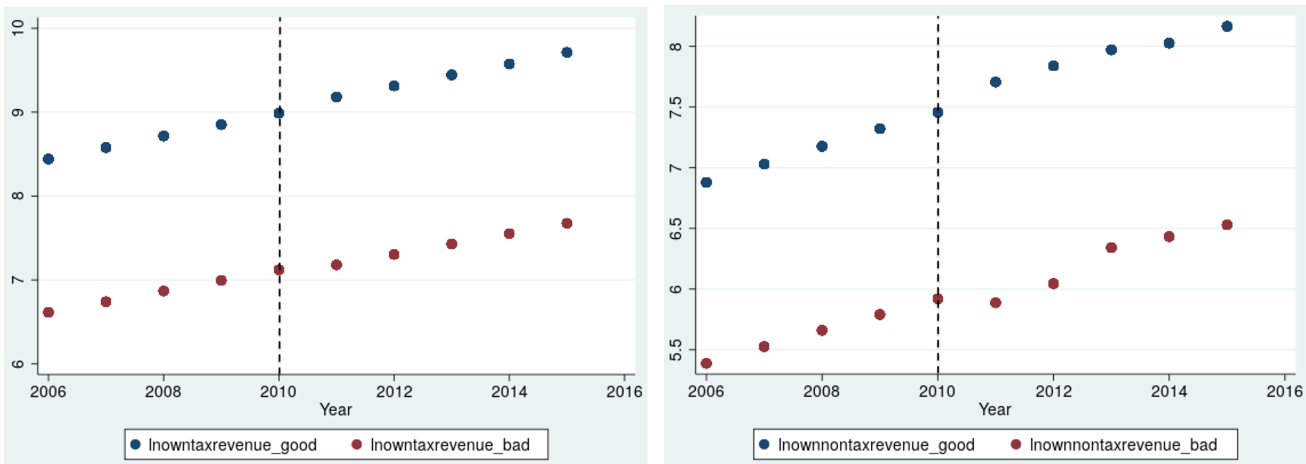
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 25. Robustness: Effect of Mechanism on Logged Own Tax and Non-Tax Revenues

	(1) LogOwnTax	(2) LogOwnTax	(3) LogOwnTax	(4) LogNonTax	(5) LogNonTax	(6) LogNonTax
Badcadre×NewMech	-0.170**			-0.179		
	(0.0822)			(0.170)		
bad15		-0.190**	-0.209**		-0.120	-0.143
		(0.0873)	(0.0914)		(0.208)	(0.208)
bad14		-0.175**	-0.195**		-0.0784	-0.102
		(0.0846)	(0.0878)		(0.205)	(0.206)
bad13		-0.169*	-0.188**		-0.114	-0.138
		(0.0828)	(0.0852)		(0.199)	(0.199)
bad12		-0.162*	-0.182**		-0.279*	-0.303*
		(0.0822)	(0.0837)		(0.160)	(0.148)
bad11		-0.156*	-0.175**		-0.303	-0.327*
		(0.0827)	(0.0833)		(0.178)	(0.160)
bad10			-0.0383*			-0.0441
			(0.0215)			(0.0736)
bad09			-0.0287*			-0.0382
			(0.0162)			(0.0586)
bad08			-0.0195*			-0.0244
			(0.0108)			(0.0417)
bad07			-0.00958*			-0.0116
			(0.00538)			(0.0224)
Constant	7.854***	7.854***	7.854***	6.400***	6.400***	6.400***
	(0.0183)	(0.0185)	(0.0185)	(0.0405)	(0.0409)	(0.0411)
Year FE	✓	✓	✓	✓	✓	✓
State FE	✓	✓	✓	✓	✓	✓
Observations	280	280	280	280	280	280

Notes: This table considers the difference-in-difference specification for logged own tax revenue and logged own non-tax revenue. This robustness exercise seeks to address concerns of tax revenue being a macro variable and having exponential growth and of differences in absolute terms between good and bad cadres' revenues. We see qualitatively similar effects of own tax revenues showing significant estimate of 15.6% divergence across good and bad cadres, while logged own non-tax revenues (placebo variable) being not significant. See Figure 57 for graph.
Standard errors in parentheses are clustered at the state cadre level
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure 57. Robustness: Effect of Mechanism on Logged Own Tax and Non-Tax Revenues.



Notes: Logged Own Tax Revenues (*Left*) and Logged Non Own Tax Revenues (*Right*) are plotted for good and bad cadres for fiscal years 2006-2015. See Table 25 for difference-in-difference analysis.

Table 26. Forgone Own Tax Revenue due to Quota Affirmative Action Policies (Counterfactual).

Year	AvgExmRnk w/out Res	AvgExmRnk w/ Res	Own Tax Rs. (crore)	Own Tax $
2015	90.5	199.2	-9250	-$1,423,155,590
2014	90.5	227.1	-11622	-$1,788,037,436
2013	90.5	191.0	-8556	-$1,316,295,256
2012	89.5	167.1	-6604	-$1,016,023,613
2011	85	139.5	-4635	-$713,033,527
2010	75	140.6	-5582	-$858,833,278
2009	66	117.4	-4378	-$673,583,429
2008	60	107.1	-4007	-$616,401,060
2007	56	89.7	-2868	-$441,298,004
2006	45	83.2	-3254	-$500,655,713
2005	44	89.4	-3864	-$594,490,716

Notes: This table shows the average exam rank across all candidates with reservation and without reservation. The counterfactual of without reservation considers the highest n_t exam ranks, where n_t is the number of total vacancies for year t. Exchange rate is assumed at 65 $\frac{INR}{USD}$.

Table 27. Forgone Own Tax Revenue due to ST Quotas (Counterfactual).

Year	AvgExmRnk w/out ST Res	AvgExmRnk w/ Res	Own Tax Rs. (crore)	Own Tax $
2015	172.3	199.2	2289.9	$352,297,205
2014	196.4	227.1	2612.9	$401,981,077
2013	153.5	191.0	3194.5	$491,455,692
2012	134.1	167.1	2806.8	$431,819,844
2011	114.8	139.4	2099.9	$323,055,143
2010	98.5	140.6	3580.9	$550,909,663
2009	76.0	117.4	3529.6	$543,008,686
2008	56.3	107.1	4317.2	$664,193,599
2007	47.6	89.7	3585.2	$551,577,286
2006	34.5	83.2	4148.4	$638,213,841
2005	37.7	89.4	4399.0	$676,763,716

Notes: This table shows the average exam rank across all candidates with reservation and without ST reservation. The counterfactual of without ST reservation replaces ST candidates with the highest non-qualifying candidates by exam rank. Exchange rate is assumed at 65 $\frac{INR}{USD}$.

Table 28. Forgone Own Tax Revenue due to SC Quotas (Counterfactual).

Year	AvgExmRnk w/out SC Res	AvgExmRnk w/Res	Own Tax Rs. (crore)	Own Tax $
2015	138.9	199.2	5128.3	$788,976,974
2014	148.0	227.1	6732.2	$1,035,723,231
2013	136.6	191.1	4633.8	$712,887,179
2012	144.1	167.1	1956.2	$300,954,126
2011	104.0	139.5	3020.0	$464,614,169
2010	93.9	140.6	3975.7	$611,650,560
2009	64.5	117.4	4504.1	$692,933,224
2008	58.1	107.1	4170.2	$641,570,342
2007	50.7	89.7	3320.9	$510,913,619
2006	31.3	83.2	4423.6	$680,550,610
2005	35.5	89.4	4590.0	$706,152,126

Notes: This table shows the average exam rank across all candidates with reservation and without SC reservation. The counterfactual of without SC reservation replaces SC candidates with the highest non-qualifying candidates by exam rank. Exchange rate is assumed at 65 $\frac{INR}{USD}$.

Table 29. Forgone Own Tax Revenue due to OBC Quotas (Counterfactual).

Year	AvgExmRnk w/out OBC Res	AvgExmRnk w/Res	Own Tax Rs. (crore)	Own Tax $
2015	177.0	199.2	1891.3	$290,974,359
2014	197.2	227	2541.5	$390,996,795
2013	175.8	191.0	1293.7	$199,026,461
2012	141.0	167.1	2219.6	$341,472,305
2011	119.7	139.5	1678.1	$258,167,861
2010	107.4	140.6	2822.5	$434,228,945
2009	86.4	117.4	2641.1	$406,323,480
2008	68.2	107.1	3310.6	$509,322,496
2007	50.1	89.7	3369.2	$518,333,466
2006	41.3	83.2	3572.0	$549,539,405
2005	34.3	89.4	4693.1	$722,010,229

Notes: This table shows the average exam rank across all candidates with reservation and without OBC reservation. The counterfactual of without OBC reservation replaces OBC candidates with the highest non-qualifying candidates by exam rank. Exchange rate is assumed at 65 $\frac{INR}{USD}$.

Table 30. Summary statistics for variables used in discrete choice analysis of preferences (in Tables 4, 5, and 6).

Variable	Mean	Std Dev	Min	Max
Distance From Home State	697.0949	380.7953	0	1637
GSDP per Capita 04-05	28906.81	9726.827	8621	49385
Health Index 08	.5988333	.0999352	.417	.817
%age Rural Roads Surfaced	.6694847	.2169275	.1226844	.989721