

MATCHING PROBLEM OF CIVIL SERVICE

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ABSTRACT. Using a matching theory perspective, we analyze the extent to which existing and alternative Indian Civil Service state assignment mechanisms can yield balance across three dimensions of interest: quality, embeddedness, and quota. We find that a recent change in the matching mechanism in 2008 has systematically skewed assignments by assigning relatively poor quality, outsider bureaucrats to *bad state cadres*: 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. By exploiting the exogenous change in mechanisms, we quantify the decrease in tax revenue for the bad cadres caused by the new mechanism and estimate the impact of exam rank on tax collection, allowing welfare analysis for counterfactual policies and mechanisms. Global balance in quality across state cadres is a unique constraint which 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.

1. INTRODUCTION

The Indian Administrative Service (IAS), often referred to as the “Steel Frame of India,” is the topmost tier of the central government civil service which administers and oversees a vast array of government operations at the state and federal levels from revenue administration, policy formulation, and public works to maintaining law and order, supervising expenditure of public funds, and implementing education and development initiatives. This paper analyzes the mechanisms used for the lifelong assignment of IAS officers to *state cadres*¹ at the very start of their careers. Motivated by the desire of the Indian Administrative Service to

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¹We use the terms “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.

live up to its *All-India* mandate and promise *well-balanced* development across all of India’s state cadres, we analyze the extent to which different IAS cadre assignment mechanisms can be successful in yielding balance across three dimensions of interest: quality, embeddedness, and quota. With the novel approach of analyzing this political economy problem using a matching theory framework, we i) underscore a new class of constraints in matching which arise in political economy: constraint for global balance in quality, ii) assess the imbalances caused by different IAS cadre assignment mechanisms, iii) empirically evaluate the effect of a recent mechanism change on state capacity, development outcomes, and bureaucratic performance, and iv) highlight welfare counterfactuals and trade-offs of alternate matching mechanisms and policies.

Every year, the Union Public Service Commission (UPSC) holds a competitive Civil Services Examination² 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. In this allocation process, only the preferences of candidates have been taken into account, making this a *one-sided market*. In addition, the government seeks to impose *balance constraints across overlapping dimensions* of embeddedness and quota, along with a *global balance constraint* of uniformly distributing talent across states. Such a constrained allocation problem arises in civil services and government personnel assignment problems across many countries. Thus the use of a matching theory framework in this political economy application has broad applicability in theoretically understanding the consequences of various matching mechanisms, empirically evaluating the effects on outcomes, and in an engineering sense, helping design and implement better mechanisms.

The IAS cadre allocation process is transparent, algorithmic, and void of subjective internal evaluations or arbitrary political influence seen in subsequent transfer or promotion processes. From the biographical information it has on each of the candidates, the UPSC incorporates the home state of origin, the quota category, and the exam rank of each candidate in the mechanism. The central government tries to avoid lopsided allocations on these three 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.” The central government hopes the bureaucracy will benefit from having some locally embedded insiders who are perhaps more willing and better able to serve the regions with which they are familiar. However, the government is also naturally wary of insiders being too familiar and falling prey to local elite capture. Hence, the UPSC has targeted a 1:2 ratio between “insiders” and “outsiders” in each 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). Hence, the UPSC sets different exam score cutoffs for each of these groups and the mechanism tries to ensure each cadre has a similar quota representation. 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, it is only natural to uniformly distribute bureaucratic quality across the cadres. We refer to this as the “quality dimension.” Hence, the assignment of IAS officers to state cadres

²See Appendix E for details on the Civil Services Examination. Note that 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; however, such promotees do not enter cadre allocation mechanism. See Appendix D for more.

is a structured allocation problem with well-defined constraints, apt for applying matching theory techniques.

Matching theory was developed as a counterpart to standard economic theory where prices and willingness to pay determine allocations. In the canonical applications of matching theory, prices are either non-existent (i.e., school choice, residency matching) or illegal (i.e., kidney exchange). This paper highlights an example of how matching theory can be applied to political economy. In a similar spirit, Thakur (2017) looks at the party-specific committee assignment mechanisms in the U.S. Senate from a matching theory perspective. The crux of that paper is the existing tenants problem, the difference in strategyproofness between mechanisms used by the two political parties, and the empirically testable predictions this implies. Instead of focusing on the strategic incentives induced by the matching mechanism, this paper highlights how matching, when applied to political economy, produces a unique set of balance constraints which tend not to arise in the canonical matching applications.

In this case, the mechanism designer is the central government which seeks to promote uniform growth and development across all Indian cadres. This implies a set of constraints with a paternalistic flavor. Apart from balance constraints over quota and embeddedness, which are similar to standard affirmative action constraints in classic matching applications like school choice, the global constraint to have balance over quality across cadres is unique. 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, rather than being manipulated by the mechanism designer. There is no attempt to correct lopsided outcomes such as the best students/residents being allocated to highly ranked, prestigious programs/hospitals. Furthermore, in our setting, such a global constraint for uniform quality requires the mechanism designer to identify and correct for many of the underlying correlations in the data amongst preferences, age, exam rank, reservation, etc, which most matching applications simply take as given. If the mechanism fails to address the underlying correlations, as we show for the recent mechanism, then allocations can cause a divergence in development outcomes, economic growth, bureaucratic performance, social welfare, and politician-bureaucracy relations across India.

In this paper, we analyze the IAS cadre assignment procedure from all aspects of matching theory: theoretical lens, empirical analysis, and engineering design. First, from the assignment data as well as from matching theory modeling, we show that the new matching mechanism used from 2008 onwards, skews assignments by systematically assigning relatively poor quality, outsider candidates to *bad state cadres*: regions which are newly formed, face external foreign conflict, and have internal political strife. These imbalances arise because the new assignment mechanism is more responsive to correlation in candidates' preferences over state cadres and because of consistent patterns of disproportionate regional representation amongst exam toppers³. Compared to the older mechanism used in 1984-2007, regional homophily has noticeably increased, with Northerners staying in Northern states, Southerners in South and IAS officers being assigned state cadres much closer to their home state. Hence the intentions of the IAS promoting national unity and integration, as envisioned by early proponents of the IAS like Sardar Patel, have been undermined. Second, we show that

³We use the terms “exam toppers,” “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.

imbalances in the assignment process also translate into imbalances in bureaucratic performance and developmental outcomes. By exploiting the exogenous change in mechanisms, we estimate the decrease in tax revenue collection for bad cadres caused by the New Mechanism. 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 collection; this allows welfare analysis for counterfactual matching mechanism designs and policies. Moreover, we 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. We show that 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. Finally, these imbalances motivate our study of how alternative mechanisms—two-sided matching, nudging preferences via incentives, and grouping cadres—can be designed to overcome such perverse, lopsided outcomes.

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 since 2008 onwards (Section 4). We analyze how and why these mechanisms cause imbalances in bureaucratic quality and national 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. We suggest various avenues to help overcome the imbalances caused by the underlying correlations in the data by changing certain mechanism features, grouping cadres, and nudging preferences (Section 6). In Section 7, we introduce two-sided matching with soft constraints motivated by cadres’ tendency to have preferences over candidates’ education, skills, and local language proficiency. Finally, we highlight the broader applicability of the matching framework to other civil services and motivate other matching applications, outside of bureaucracies, which call for incorporating quality constraints (Section 8).

2. THE INDIAN ADMINISTRATIVE SERVICE

The IAS, along with other elite civil services like the Indian Foreign Services and Indian Police Services, evolved from the Indian Civil Service, which was used by the British empire to administer the Indian colony (1893-1946). Under the 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 just roughly 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, these events are rare, and 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 the years, IAS officers are transferred across districts and promoted to higher positions of Joint Secretary of Ministries or Cabinet Secretary based on seniority, internal performance evaluation, and political influence due to ministerial involvement. 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 empanelment⁴ to the Centre. Hence, working with state civil servants, state and federal politicians, IAS officers serve in the highest-tier administrative positions from overseeing agricultural policy, land revenue and district administration, to working with NGOs to administer rural development projects or setting higher education policy.

3. LITERATURE REVIEW

Instead of providing an overarching review of the theoretical and empirical literature on bureaucracies⁵, we choose to 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. Although IAS officers are career civil servants with lifetime appointments and job security meant to insulate the bureaucracy from the whims of political instability, Iyer and Mani (2012) emphasize the vast discretion over transfers and promotions which lies in the hands of the state ministers. This “Transfer Raj” creates incentive problems. The probability of an IAS officer being transferred increases by around 10% when a new minister is elected. Furthermore, high-skilled officers (top 20 exam rank) 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. Politicized transfers cause underinvestment in skill acquisition and can have lasting detrimental consequences for economic development. 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 (reasonably exogenous shock as this occurs when the Member of Parliament seat comes under an affirmative action

⁴Empanelment 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. The selection under the Central Staffing Scheme relied on performance evaluations, systems which have changed over time: Annual Confidential Reports (until 2007), Annual Performance Appraisal Reports (2008-2015), and 360 Degree Appraisals (2015 onwards).

⁵Theoretical 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). For a review of survey analysis related to bureaucracies and civil services see Rogger (2017). For a review of field experiments in personnel economics, see Finan et. al (2017). For a review of work on state capacity and its impact on development, see Bandiera et. al (2014).

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 a well-specified matching algorithm. Hence, we do not have to worry about political influence.

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, higher non-tax revenue, and more development expenditures— all government functions IAS officers oversee. Hjort et al. (2015) use a value-added estimation framework, and find that education, local language proficiency, and direct recruitment predict higher value-added officers. Moreover, high value-added bureaucrats predict better project outcomes, higher luminosity (measures of nighttime lights), and increased likelihood of future empanelment. Finally, Bhavnani and Lee (2015) find that locally embedded 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.

We use all 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 revolved largely 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, whether it is the National Resident Matching Program in the US (NRMP) or Japan (JRMP), tends to be an imbalanced market with more hospital vacancies than domestic candidates. Furthermore, candidates tend to have correlated preferences with a bias in favor of 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-served⁶. Roth (1984, 1986) establishes the seminal Rural Hospital Theorem, proving that when candidates have strict preferences, any hospital that fails to fill its vacancies at some stable matching, will not only fill the same number of candidates, but will also be filled by the

⁶See Roth (1984, 1986) for NRMP and Kamada and Kojima (2014) for JRMP.

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. Recently, Kamada and Kojima (2014, 2017) have theoretically analyzed how to incorporate distributional constraints in the form of regional caps in two-sided matching⁷. The JRMP imposed regional caps where multiple hospitals belonged to the same region and set upper bounds on the number of vacancies which could be filled across the region. Kamada and Kojima (2014, 2017) showed that the JRMP mechanism of doctor-proposing Deferred Acceptance with hospital-specific caps (which added up to the regional cap) was both inefficient and unstable. Instead, their Flexible Deferred Acceptance Mechanism—combining hospital-specific artificial caps with hospitals taking turns in a pre-defined order to fill vacancies to meet regional caps—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. Kamada and Kojima (2017) characterize when the constraints guarantee the existence of strongly stable matchings. In our paper, since the market is balanced⁸ 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.

In school choice and many other applications, affirmative action and legally mandated quotas/reservations for gender, race, or socio-economically under-privileged students are quite common constraints which must be accommodated⁹. This literature highlights two important considerations for incorporating such constraints in two-sided matching. First, these papers collectively highlight the differences in using hard bounds (i.e., explicit quota-reserved seats) versus soft bounds (i.e., priorities for quota candidates). Second, 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.

The literature on controlled school choice was initiated by Abdulkadiroglu and Sonmez (2003) who showed that Deferred Acceptance and Top Trading Cycles mechanisms could be modified to allow for affirmative action on a single dimension with type-specific quotas. However, Kojima (2012) showed that even when there are just two student types (minority and majority), such upper-bound quotas for majority students can hurt minority students because majority candidates who are turned down when the upper-bound quota is binding cause increased competition with minority at other schools. Instead of imposing hard upper-bounds with majority quotas, Hafalir et al. (2013) suggested soft lower-bounds with minority student reserves. Under such a scheme, if the minority reserve set by a school is not met, then any minority candidate is preferred to any majority candidate at that school. However,

⁷See Kamada and Kojima (2014) for a discussion on other examples of similar regional caps and distributional constraints which arise in UK medical match, Scottish Teacher allocation, college admission in Hungary and Ukraine where there are state-financed and privately-financed seats, and Chinese graduate school admissions where there are professional and academic programs.

⁸The UPSC chooses exactly the correct number of IAS candidates from the examination as there are vacancies.

⁹See 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).

if there aren't enough minority candidates to fill the reserve, then majority candidates can fill the remaining vacancies. Hence, their Deferred Acceptance algorithm with minority reserves pareto dominates the Deferred Acceptance algorithm with majority quotas. Ehlers et al. (2014) further generalize the notion of soft constraints to an arbitrary number of student types where schools have both ceilings and floors for each student type. Their generalization is substantial, because unlike Hafalir et al. (2013), the mechanism designer cannot simply split the school into clones with one prioritizing minority students and other with the number of vacancies lowered by the minority reserve. Instead, they propose to control the soft ceilings and floors dynamically to achieve fair and non-wasteful allocations.

Our paper differs from canonical school choice literature because when we introduce two-sided matching, it is with the intention of incorporating cadres' preferences over candidates on the basis of local language proficiency, education and skills. Public schools on the other hand legally cannot have preferences over students. In practice, this global indifference is broken first by "priorities" (i.e., sibling also goes to school, distance of school, house on school bus route) and then by random lotteries. Hence, the affirmative action restrictions are also often incorporated through priorities in these applications. 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. Furthermore, in our setting, the IAS constraints are across overlapping dimensions of exam rank, embeddedness, and quota. Kurata et al. (2017) is the closest paper which deals with overlapping types. They show that applying the same notion of stability as the model with disjoint types can lead to non-existence of stable matching. Instead, they propose Deferred Acceptance for Overlapping Types which guarantees stable matching, is strategyproof, and obtains the student optimal matching. However, our two-sided matching is motivated by the desire to accommodate cadres' preferences over candidates and moreover, the global constraint of uniform quality across cadres is a novel constraint in this setting.

We further discuss and implement the results from this literature on matching with constraints in Section 7, when we introduce two-sided matching with reservations for insiders and quota candidates.

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 initial assignment of IAS recruits (and other civil services) to states. The two most recent systems are the 1984-2007 system (Section 4.1) and the 2008-present system (Section 4.2). We will show that the New Mechanism causes imbalances in quality, systematically hurts 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).

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

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)

4.1. The 1984 “Old Mechanism.”

The Old Mechanism was in place from 1984 to 2007¹⁰.

- (1) The 24 cadres are split into 4 alphabetically ordered groups¹¹:
 - 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)¹².
- (4) Candidates are arranged by exam score and each candidate is asked whether or not he would like to be considered for an insider position¹³.
- (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.
- (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 category¹⁴.
- (7) If an insider vacancy remains even after swaps, convert it to an outsider vacancy.

¹⁰The official assignment process rules are clearly delineated by the UPSC and are available online at <http://persmin.gov.in/AIS1/Docs/OldCadreAllocProcedure.pdf>.

¹¹This 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.

¹²Because 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.

¹³We do not have the answer to this willingness to be an insider question by candidate, hence in our simulations we make the assumption 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.

¹⁴During the swaps, insider disabled candidates are given highest priority, however, we omit this from the simulations.

- (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 onwards¹⁵. 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 cadres¹⁶ ¹⁷. 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)¹⁸.
- (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.
- (4) Next, if insiders don't 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 outsider¹⁹ (if this doesn't 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.

¹⁵The official assignment process rules are clearly delineated by the UPSC and are available online at <http://persmin.gov.in/AIS1/Docs/NewCadreAllocPolicy.pdf>.

¹⁶Since we don't have the candidates' preference ranks, for our simulations, we make various assumptions and randomly simulate preferences: (1) “Block:” want to be insider, followed by random within block of good cadres, followed by random with block of bad cadres. (2) “Uncorr:” want to be insider, followed by uncorrelated preferences over remaining cadres. (3) “Close:” cadres in order of closest distance from Home State's capital city. (4) “Res3:” same as Block, but force every 3rd choice to be from bad cadre group.

¹⁷Caveat if truncate 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.

¹⁸Because 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.

¹⁹In reality, the counterfactual is run using the preferences indicated, however, in our simulations, as an approximation, we run the counterfactual with a random preference we generate by assumption because we don't have the actual preference orders of the candidates.

- (6) In order of exam rank, run through each candidate's preference order and allocate if vacancy exists^{20 21}.

4.3. Distributional Asymmetries and Their Causes.

4.3.1. *Systematic Imbalances due to the Mechanisms.*

A common feature of both the Old and the New Mechanisms is the priority given to insider candidates. The Old Mechanism goes through candidates in order of exam ranks, and if a candidate is willing to be an insider and there is a relevant vacancy, the seat is allocated. Next, in the order of exam rank, those willing to be insiders are given yet another chance to be allocated to their home state if vacancies across categories can be swapped. Finally, each insider candidate is placed in subsequent cycles of 1:24, and the outsiders allocated to the state only come from cycles after the initial cycles which insiders occupy. This means that insiders will tend to be of a higher quality than outsiders, and the more insider vacancies a state is able to fill, the worse exam rank their outsider officers will be. The New Mechanism works similarly, except for the 1:24 cycles. After insiders are allotted and swaps are incorporated, the mechanism goes in order of exam rank in remaining candidates and goes on matching preference rank orders with vacancies. We see from Figure 4, that across both mechanisms and across each quota category, there is a large discrepancy in the exam ranks of insiders versus outsiders. These differences have grown with the New Mechanism for two reasons. First, correlated preferences in the New Mechanism (outsiders are no longer allocated in 1:24 alphabetical order, but instead the mechanism goes through preferences of candidates in order of exam rank). Second, the number of direct recruits has steadily increased from 87 in 2005 to 180 in 2015. Thus, the lower ranked toppers who qualify amongst the final list of candidates have lower exam rank.

The systematic imbalances across state cadres arise in the New Mechanism when we compare the average exam rank of candidates assigned to each cadre (Figure 5). First, the difference between the highest average quality state and lowest quality state increases from 38.4 to 144 in 2005-07 to 95 to 543. Moreover, for years in the New Mechanism (2008 onwards), the lowest quality states are consistently the same: Manipur, Tripura, Nagaland, Sikkim, Assam-Meghalaya, Chhattisgarh,... This systemic asymmetry in average quality of assigned candidates by cadres along with certain states consistently getting relative lower quality candidates arises within all quota categories: General, OBC, SC, and ST (Figure 7).

Moreover, the variance across cadres of average exam ranks of assigned candidates jumps by about 5-fold in the New Mechanism compared to the Old Mechanism years (Figure 6). Hence inequality across cadres as to the quality of incoming IAS officers has grown. In fact, the variance increased even further from 2013 to 2014 when Telangana separated from Andhra Pradesh and the joint cadre Manipur-Tripura split.

The ratio for insiders to outsiders is targeted at 1:2, and cadres' posted vacancies each year are adjusted to reflect this balance. Figure 8 documents the average percentage of

²⁰Caveat 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.

²¹It is not specified what assumption is made if the vacancy quota doesn't 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.

insider requests (Left) and insider assignments (Right). We see that percentage of requests for insiders lie across all states in the narrow range of 25% to 40%. Assignments on the other hand, are capped at around 33%, while in the New Mechanism years, states like Nagaland, Sikkim, West Bengal, Chhattisgarh, Assam-Meghalaya all get less than 20% insiders. A similar asymmetry existed even in the Old Mechanism years, because many of these states are able to place relatively few candidates in the toppers list (Figures 15 and 16). Given the difference in average rank between insiders and outsiders we highlighted above, this partially explains why these states get lower average exam rank overall.

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 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.

To further highlight the systematic under-performance of the bad cadres, we simulate two mechanisms: completely random assignments and random assignments within quota²². In Figure 9, 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 random and random with quota mechanisms where as the New Mechanism vastly under-performs relative to the random mechanisms. In Figure 11, we calculate for each cadre, the percentage of time its actual average exam rank is above the average exam rank produced by Random within Quotas mechanism simulations. Hence, the orange line at 50% implies the state is assigned an average quality similar to random. 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 cadres tend to switch around across years from under-performing to over-performing. The rotation of groups across years causes this equalizing effect across time. However, starting from 2008 onwards, with the New Mechanism, the bad cadres consistently tend to under-perform relative to random

²²The 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.

Figure 2. The circled regions are cadres which are 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.



assignment. Figure 10 highlights this by plotting performance time-series for a subset of the good and bad cadres. Comparisons with the completely random mechanism produce similar results.

Using a difference-in-difference strategy, we estimate the overall effect of the change in mechanism on quality is bad cadres receiving candidates who are 114.8 exam ranks lower on average, or .784 standard deviations lower than national average (Table 1 and Figure 13).

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.

The imbalance by cadre in terms of placing candidates amongst the exam toppers chosen for IAS is an old problem present in the Old Mechanism as well, but it has been made worse in the New Mechanism because candidates' preferences are now taken more seriously. Figure 14 shows how the bad cadres all have few toppers relative to their total vacancies. Since the coveted 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. And since both Old and New Mechanisms favor insiders by giving them first priority, this puts many of the bad cadres at a comparative loss. As Table 2 emphasizes, the correlation between this ratio of toppers to total vacancies and exam rank was -0.03 for 2005-07, but became highly negative at -0.55 in 2008-13 and

-0.35 in 2014-15 under the New Mechanism. Bad cadres tend to place fewer toppers, and moreover, lower quality toppers within all quota categories (Figures 15 and 16).

Although we do not have the candidates' preference rank orders from the New Mechanism, the claim that candidates have correlated preferences with a reasonable consensus over which cadres are good/bad can be corroborated using the Benbabaali (2008) survey of IAS officer's top 5 (Figure 17 Left) and bottom 5 (Figure 17 Right) cadre preferences²³. The states ranked amongst the top 5 map well to those we call good cadres, while the states ranked amongst the bottom 5 map well amongst those we call 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 tribes²⁴. Jammu and Kashmir involves disputed territory struggles with Pakistan, while West Bengal has internal struggles with Naxalite factions.

4.3.3. *Discrete Choice Analysis of Cadre Preferences.*

The quality balance constraint necessitates a closer inspection of correlation in the preferences. Since outside of the home cadre ranking (which is a strategic ranking due to the insider priority), the serial dictatorship based New Mechanism is strategyproof, we use discrete choice methods to understand the calculus behind the IAS officers' rank-order preferences for non-home cadres.

We have data for 122 IPS officers each rank-ordering 24 cadres data from the 2008 batch. We find that in ranking the top 5 alternatives, proximity (distance from home state and insider state), infrastructural development/development capacity (percentage rural roads surfaced) and GSDP per capita is given importance, while the coefficient on health index, though positive, is not significant (Table 4 column (1)). Amongst the bottom 5 preferences, proximity, infrastructural development and health index are important whereas GSDP per capita is not significant (Table 4 column (2)). This finding corroborates 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 plays a role in ranking the very bottom of the list.

Next, we consider the entire preference rank order. The appropriate empirical methodology to deal with such discrete choice data is to use rank-ordered logit (Table 4 columns (3) and (4)), using which we find that proximity, GSDP per capita, health index, and infrastructural development are all factors which civil servants reward positively²⁵. In column (4) of Table 4, we also add a second-order term for distance from home state squared, which also appears negative. Thus, we find that the effect of proximity on utility is convex.

Underlying the rank-order logit is a latent utility specification where we can understand the relative weights civil servants place on the various measures. In understanding the relative

²³Quoting 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."

²⁴Benbabaali (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 common (mis-)perceptions.

²⁵A simple linear regression also finds the same directionality across all the variables (Table 4 column (5)). However, we prefer the discrete choice approach given the rank-ordered preference data.

importance of these different dimensions it is imperative to consider the relative variability in the data, so we measure in terms of 1 standard deviation effects. Relative to 1 standard deviation increase in Distance from Home State, are 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 3 (3)). This suggests that proximity (particular effects from being an insider in the state) is by far most important, followed by development, and lastly, standard of living. When we compare the magnitudes from the conditional logit for the top 5 (Table 3 (1)) and bottom 5 (Table 3 (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.

We interpret the percentage rural roads surfaced as a measure of infrastructural development or state capacity, so it is interesting how this measure is rewarded in the preference rank orders of the civil servants. Perhaps their effectiveness or efforts can be rewarded in locations where they are able to deliver services.

All of this analysis corroborates anecdotal interviews with IAS officers, who say that the top of the ranking involves ranking amongst neighboring states (proximity considerations), amongst which differentiation may be based on culture, language, and wealth or standard of living. However, after that, the lower ranking is done on the basis of proximity and development²⁶

We can also do the exercise of comparing the average distance candidates are willing to travel to get a certain cadre relative to the average cadre. For this calculation, we calculate the latent utility for each candidate for each cadre. Then we compute the average utility for each candidate across all cadres, and take the difference in latent utilities as a factor of the coefficient on distance. This gives us for each candidate, the amount of miles he would be willing to travel for any cadre relative to average cadre. We take the average across candidates for each state cadre and report in Table 7.

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

Since there is a quality balance constraint and an imbalance in the production of exam toppers by cadre, it is imperative to understand where exam toppers originate from, since insiders are given priority in the mechanisms. Analysis using Poisson regression to handle data on counts of exam toppers from different cadres, finds that 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 column (1)). Even if we split by rural and urban literacy, both coefficients are negative and replacing literacy with the education index used in calculating HDI, we find a negative coefficient (Table 8 columns (2) and (3)). From the data we see that some of the highest topper producing cadres have amongst the lowest literacy rates (Bihar, Uttar Pradesh, Rajasthan). In these places, despite lower literacy rates, there is a culture of valuing civil service positions. We should not be hasty in determining that the civil service exam doesn't capture literacy, but instead, we should note that literacy alone does not produce the effects. In fact, in India, comparatively, literacy rates are pretty high in the Northeast, from where there are very few successful toppers. And even the highest literacy cadre—Kerala—produces many toppers, but not nearly as many as Uttar Pradesh, Rajasthan, and Bihar.

²⁶It is anecdotal findings and this empirical analysis which motivates using Block Preferences for our simulations.

The vast imbalance across cadres as to their ability to produce exam toppers is apparent from our estimated probability distribution functions shown in Figure 12.

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

In India's Deputy Prime Minister Sardar Patel's famous speech to the Constituent Assembly in October 1949, where he advocated for establishing the Indian Administrative Services which was 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." Sardar 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, be promoted or empaneled 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 regional grouping. As seen in Figure 18, percentage of homophily has jumped relative to continuing with the Old Mechanism (dotted line). When separated into homophily just amongst Southerners (Figure 19 Left) and amongst Northerners (Figure 19 Right), we see that both have jumped with the advent of the New Mechanism relative to the Old Mechanism counterfactual (dotted line), but homophily amongst Southerners has particularly sky-rocketed. The regional divide between northern and southern states is embedded in cultural similarities within the two groups and also because 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 (Figure 20 Left) and the variance (Figure 20 Right) of these distances across individuals has also fallen relative to the Old Mechanism counterfactual (dotted lines)²⁷. These patterns motivate one of our preference assumptions we use for simulations in future sections: "Close" models candidates ranking preferences over cadres by the distance from their home cadre.

4.4. **Who benefits and who loses?**

We already showed above that the New Mechanism adversely affects the bad cadres. By the zero-sum nature of the problem, the New Mechanism thus also systematically benefits the good cadres. Good cadres are able to produce a healthy supply of exam toppers (i.e., insiders) 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 answer to these questions depend on the degree of correlation in preferences. Given the high correlation in preferences we observe 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 21 top row). However, if there is sufficiently low correlation in preferences, all quartiles of candidates could be better off with the New Mechanism (Figure 21 bottom row). The Old Mechanism's policy of not incorporating complete preference rank orders and

²⁷Distance between cadres is measured by distance in miles between capital cities.

imposing group rotations allowed both top scorers to be assigned to less preferred cadres and low scorers to be assigned highly popular cadres. Under the New Mechanism however, correlated preferences produce competition for popular, highly sought after cadres, and hence exam toppers fill up these vacancies, leaving bottom quartile candidates worse off²⁸. 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 attempt to evaluate whether these systematic imbalances documented above have detrimental consequences for state capacity, developmental outcomes and bureaucratic performance. In Section 5.1, 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. We are then able to use our estimates to evaluate counterfactuals such as 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 involvement²⁹, and career trajectories and specializations within the IAS are vastly different by individuals³⁰, 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/Magistrate³¹. Hence all IAS officers start their careers with the same primary job responsibility: revenue administration³². 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 the institutional details of the IAS, we measure the 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.

²⁸Understanding these heterogeneous effects can also highlight which coalitions might have stood for/against the endogenous change in the mechanism. Such analysis speaks to economics and organizational behavior literature which posits theories of endogenous change in institutions (for example, Knott and Miller (1987)).

²⁹Iyer and Mani (2015).

³⁰Ferguson and Hasan (2013).

³¹Early 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.

³²Later 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.

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) and total tax revenues (defined as own tax revenue + non-tax revenue) seem to move in line with our expectations (Figure 22 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 do not control, should not show such a divergence (Figure 22 top right)³³. 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 significant³⁴. 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 24)³⁵. This gives us comparable estimates of Rs. 5330.9 crore (\$820 million) lower own tax revenue³⁶ for bad cadres relative to good cadres, and insignificant effect on the placebo non-tax revenues (see Table 11)³⁷.

Furthermore, using the change in mechanism as an instrument for the average quality of assigned IAS officers to a cadre³⁸, we find that 1 lower exam rank corresponds to Rs. 85.11 crore (\$13 million) lower own tax revenue (Table 10 second column). Since we exploit the exogenous change in cadre allocation mechanism in this IV approach, our empirical strategy alleviates the simultaneity problem which arises when trying to estimate the effect of exam rank on outcome variables.

³³The jump in Figure 22 appears because of Maharashtra and Haryana. See Figure 23 for robustness excluding these cadres.

³⁴See Table 12 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.

³⁵The jump in Figure 24 appears because of Maharashtra and Haryana. See Figure 25 for robustness excluding these cadres.

³⁶The structural break strategy gave a difference in linear trends of Rs 1336.6 crore, which translates to New Mechanism treatment effect of $1336.6 \times (1+2+3+4+5)/5 = \text{Rs. } 4009.8$ crore due to 5 ("post-treatment") years under the New Mechanism.

³⁷See Table 12 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.

³⁸The 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 1.

Thus, exam rank appears to be indicative of bureaucratic performance³⁹. 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 13 we see that the forgone own tax revenue due to reservation policies in 2015 was around Rs. 9,250 crore (\$1.4 billion)⁴⁰. To put this in perspective, the total own tax revenue for all these states in 2015 was \$118 billion, using exchange rate $65 \frac{INR}{USD}$. Similarly, we can quantify the yearly forgone own tax revenue due to each quota category⁴¹: 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 (Tables 14, 15, and 16).

5.2. Impact on Development: Human Development Index. 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) implement development policy (chief development officer role). In Section 5.1, we emphasized role ii), which is a shared responsibility for all at early stages in IAS career. Here, we analyze role iii) which was emphasized during the transition from Indian Civil Services under British rule, to the Indian Administrative Service under independent India. 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, development roles are specialized across different posts and each IAS officer has 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 0.0488 lower HDI compared to good cadres (Table 17). Since HDI is not calculated on a very regular basis, although the difference and difference specification seems motivated by convincing parallel trends in Figure 26, we treat this finding with some important precaution.

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

Bertrand et al. (2015) circumvent incentive problems in internal evaluations by using their own surveys of local media, businesses, NGOs, politicians and other civil servants to form their own measure of perceived bureaucratic effectiveness. They find that exam scores predict perceived bureaucratic effectiveness, so the skewed distribution in entrance exam scores by cadre resulting from the New Mechanism is troubling in and of itself. Furthermore, they find that officers who are older and enter with a large cohort within the assigned state exhibit lower perceived bureaucratic effectiveness. They argue that this is because older candidates

³⁹Existing 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)).

⁴⁰This counterfactual calculation averages exam rank across all candidates, and assumes all N candidates are filled by the N highest exam scorers rather than by lower affirmative action exam cutoffs for OBC, SC, and ST.

⁴¹The counterfactual calculation 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.

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 .47 years older than those assigned to good cadres (Table 18 column 1)⁴². This is driven by the positive correlation between age and exam rank (i.e., older candidates tend to perform worse on the entrance exam). Since the New Mechanism assigns lower exam rank candidates to bad cadres, the externality of assigning older candidates follows indirectly. Moreover, it must also be noted that the IAS cohort size has consistently increased from 87 vacancies in 2005 to 180 vacancies in 2015, so cohort sizes have grown consistently in the recent years. Furthermore, the upper age limits and maximum number of attempts at the UPSC exam have also consistently been relaxed in recent years⁴³. Hence, bad cadres will tend to have IAS officers with lower perceived bureaucratic effectiveness scores, adversely affecting economic performance, development outcomes, and local perceptions of bureaucracy by media, business, and politicians.

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. 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%⁴⁴. Figure 27 shows that while the Old Mechanism (in blue 2005-2007) was allocating between 25-30% of top 20 scorers to bad cadres⁴⁵, the New Mechanism (in blue 2008-2015) has dropped drastically to near 0%. By simulating the counterfactual if the Old Mechanism was continued in years 2008-2013 maintaining the assumption that everyone wants to be an Insider (red line), we see that a much higher percentage of the 20 highest exam scorers would have been allotted to bad cadres. Hence, the Old Mechanism would lead to a more equitable posting of high ability officers across cadres and hence a more equitable distribution (across cadres) of politicized transfers. On the other hand, in light of Iyer and Mani (2015), the bad cadres will have IAS officers facing increased posting variability in a response to political changes.

Bhavnnani 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, and local language proficiency correlates positively with being an insider. From Figure 28, which shows the difference between insiders requested and insiders assigned as a percentage of total requests, we see that because the bad cadres

⁴²We use Column 1 estimates which drop the state of Sikkim from the sample, as with just one vacancy per year, this is a high variance state. Particularly in 2011, Sikkim is allotted a 25-year old which makes it the state with the lowest average age across all states.

⁴³Current 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.

⁴⁴To put into perspective, Iyer and Mani (2015) find that the baseline transfer probability for an IAS officer in any given year is 53%.

⁴⁵Around 30% would be natural as 7 out of 24 cadres we have identified as the under-performing bad cadres.

tend to produce fewer exam toppers, they face a shortage of insiders. Hence, bad cadres might have lower public good provision and relatively lower value-added bureaucrats as measured by worse project outcomes, lower luminosity, and decreased chance of future empanelment.

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 -.14 and -.37 between being a bad cadre and the average number of trainings completed. This might suggest that bad cadres are assigned less capable candidates with a lower likelihood for promotion. Or as Mani and Iyer (2015) suggest, bad cadres may be assigned candidates who choose to focus on political loyalty rather than skill acquisition for career advancements.

Finally, we see that bad cadres historically (2001-2007) tended to rely more heavily on promoted state civil servants compared to good cadres: 7.5% more promotees compared to direct recruits, 8.2% more promotees relative to authorized strength, and 15.6% fewer direct recruits relative to authorized strength (see Table 19)⁴⁶. However, in recent years since the change in the mechanism, the bad cadres are shifting towards relying more heavily on direct recruits compared to the good cadres. Across 2008 to 2017, bad cadres use only 5.1% fewer direct recruits relative to their authorized strength compared to good cadres and only 4.9% more promotees. Hjort et al. (2015) find that on average, direct recruits predict higher value-added, however, a more in-depth analysis must be conducted to compare the relevant tradeoff between using direct and indirect recruits for bad cadres, given that they are allotted below-average quality direct recruits. Nevertheless, it is imperative that the imbalances caused by the New Mechanism be addressed.

6. ALTERNATIVE ONE-SIDED CADRE ALLOCATION MECHANISMS

6.1. An Approximate Ranking of One-Sided Cadre Allocation Mechanisms.

Despite the complicated 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 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.

Let us start with the Old Mechanism which addressed many of the correlations in the data. First, the only input from the candidates is whether or not they were willing to be an insider, hence the correlated preferences across the entire rank order of preferences are avoided. Second, balance in assigned quality across time is guided by the rotating groups and the 1:24 cycles. Finally, the asymmetry caused by the origin of toppers being concentrated in certain states and quota candidates having lower exam rank causes some imbalance because of the priority given to insiders and quota candidates, but this is alleviated by the 1:24 cycles.

If we keep the structure of the Old System but ignore insider-outsider distinctions and quota constraints, we would break even the asymmetries arising from origin of toppers and lower exam rank amongst quota candidates in the Old Mechanism. This portrays how targeting balance across the embeddedness and quota dimensions is a constraint in this setting.

⁴⁶This data is from Appendix I of the 2001-2017 Civil Lists.

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

	Origins of Toppers	Correlated Pref	Quota ExmRnk	Equalizing Over Time
Old Sys w/out Insider, Quota				
Old System				
Old System w/out Rot.				
Random w/ Quota				
Completely Random				
Insiders 1st, Outsiders Rand				
New System				
All Preferences				

Scale:

Addresses	Somewhat Addresses	Fails to Address

On the other hand, if we consider the Old Mechanism without rotating groups across years, 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 across 4 years.

Next, if the 1:24 cycles were eliminated, and randomly allocate candidates within quotas (i.e., randomly assign quota candidates to their respective quota seats and then pool remaining candidates with non-quota candidates and randomly assign to remaining vacancies). The 1:24 cycle imposed structure to prevent bunching on quality in certain cadres. The Random within Quota mechanism allows for such bunching and introduces the possibility of multiple lower quality candidates randomly assigned to one cadre, hence the performance on the quota-exam-rank dimension is slightly worse.

Subsequently, if we assign candidates randomly, 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 atleast being distributed based on the roster of vacancies, but now even this leveling control is removed, leading to higher variability amongst average exam rank across cadres.

Now if we go through 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, the mechanism introduces the correlation coming from the origin of toppers because insiders are given preferential treatment and this isn't compensated for in the mechanism. For example, in the Old Mechanism, when an insider who tended to have high exam rank was allotted to a cadre, the outsider would be allotted from the next 1:24 cycle and hence would tend to have a lower exam rank. Such a balancing effect is absent from this mechanism. Furthermore, the correlated preferences problem could be made worse depending on whether we assume candidates from bad cadres would rather prefer a random outsider assignment relative to a insider position or not. For simplicity, we have made the conservative assumption in our simulations that all candidates have their home cadre as their first choice. This is a strong assumption that

works against the claims we make in this approximate comparison. Finally, random outsider assignment still allows for bunching of poor exam rank candidates as we had above.

Further tweaking the mechanism to first go through insiders and swaps, and then go by exam rank through preferences of outsiders, we get the New Mechanism. This further introduces correlated preferences in the outsiders which we were previously assigning randomly. Moreover, the origin of toppers (and hence their preferences) further skews the distribution because assuming preferences are similar geographically, if we have more toppers from the same cadres at the top, their preferences will be even more correlated.

Finally, we can construct a mechanism where all candidates are simply ranked by exam score and allowed to choose based on their ranked preferences (i.e., serial dictatorship where order is exam rank). This makes the correlated preferences problem even worse because now we introduce correlated preferences amongst even those who would have opted for insider positions in the previous mechanism.

This approximate ranking is reflected in the t-statistic comparisons⁴⁷ between these simulated alternative mechanisms and the actual assignment data in Figure 29. Moreover, in Figure 30, we see that this approximate ranking is also reflected when we compare percentage of lower means (Left), lower variances (Right), and both lower mean and variance (Bottom) with alternative mechanisms as compared to actual assignments⁴⁸. It is important to note that our maintained assumption when simulating preferences that candidates rank their home state first causes the All Preference mechanism to perform similarly to the New Mechanism which prioritizes insiders. Relaxing this strong assumption will further exacerbate the performance of the All Preference mechanism.

Although 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, as expected, the rotations in the Old Mechanism work to equalize average exam rank across cadres over time by prioritizing different states in the 1:24 cycles across time.

Lastly, we discuss some general properties of these matching mechanisms. Since the mechanisms are one-sided, they will generically violate stability to the extent cadres have preferences over candidates. So we focus instead on Pareto optimality. We also consider strategyproofness of the mechanism to understand if candidates are incentivized to truthfully reveal their preferences.

Only the All Preferences mechanism is pareto optimal since it is a serial dictatorship with order being exam rank. All other mechanisms described above have some random or arbitrary features which could admit pareto improvements given some candidate preferences.

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

⁴⁸Note that despite the variance being higher with the Old Mechanism without insider-outsider and quota constraints (red with star line), this mechanism causes a drastic improvement in the mean the extent to which isn't captured by these figures (see t-statistic comparison in Figure 29 instead).

For example, the mechanisms which prioritize insiders first, can lead to pareto-improving swaps between insiders and outsiders. Or, if there is a surplus of insider candidates relative to vacancies in a certain quota category, then there might be pareto improving swaps where the insider who got the seat swaps with the outsider's seat. Such pareto improving swaps between insider and outsider seats can occur if candidate's true preferences are such that they prefer the insider seat to a random lottery over an outsider seat, but do not rank their home state as their first choice. This leads them to report "Yes" when asked whether they want to be considered for insider seat, despite their home state not being their top choice.

As for strategyproofness, the mechanisms that don't incorporate preferences of candidates are trivially strategyproof. The Old Mechanism with or without rotation would theoretically not be strategyproof because with perfect information, the candidate would evaluate what he would get with and without reporting "Yes" on the insider question. However, practically, this requires knowing a lot of information which seems unreasonable. In our preference simulations, we assume for simplicity that all candidates' true first choice is their home state which makes the mechanisms strategyproof. In casual conversations with IAS officers, we find that they often consider the insider question asked in the Old Mechanism as a choice between saying "Yes" and potentially getting an insider seat in a state you know beforehand versus saying "No," which is associated with basically a random assignment given the burden of information required to know the counterfactual. Hence, a vast majority of candidates used to respond with "Yes." The All Preference mechanism is strategyproof as it is a serial dictatorship with order being exam rank. However, the New Mechanism is not strategyproof because similar to the Boston Mechanism, there is scope to be strategic by placing your home state at the top and being prioritized for an insider position despite your true first choice being for another more popular state, because you might not get this popular state and then have be allotted to a cadre which is must lower in your preference rank. It is important to note that restricted to the subset of non-home state cadres, preference order ranking is strategyproof under the New Mechanism, as it is based on a serial dictatorship by exam rank.

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. Moreover, this approximate ranking highlights 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 more weight the mechanism assigns, the more lopsided allocations will tend to be. For example, the Old Mechanism pays minimal heed to candidates' preferences while the New System takes preferences very seriously. Second, given the concentration of exam toppers from certain states, 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. Just by allocating insiders first before randomly assigning outsiders, there is a drop in the performance of assigning uniform quality. 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 can actually be 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 performance can sometimes be improved by relaxing quota priorities.

6.2. Grouped Cadres.

The choice of certain states to be represented as a unified group (“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 strange 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, we see in Figure 32 how the exam toppers tend to originate predominantly from certain states/territories in each of these joint cadres. From 2005-2015, 74% of AGMUT toppers were from Delhi, 73% of Assam-Meghalaya toppers were from Assam, and 87% of Manipur-Tripura toppers were from Manipur. On the flip side, in Figure 33, we see the relatively large asymmetries in toppers from the new states (Uttarakhand, Jharkhand, and Chhattisgarh) relative to their counterparts (Uttar Pradesh, Bihar, and Madhya Pradesh). It turns out that the ratio of toppers (i.e., potential insiders) relative to vacancies for a given cadre is an important determinant of average exam rank (due to the preference for being an insider). 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 20). 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 quality as well, where candidates from mother states have lower average exam ranks than new states (Figure 33). Similarly, patterns arise with Delhi and Chandigarh in AGMUT and Assam in Assam-Meghalaya (Figure 34).

Finally, we see the impact of the splitting joint cadres with the Manipur-Tripura breakdown and the separation of Telangana from Andhra Pradesh in 2014 (Figure 5). It is important for the grouped cadres to have poorly performing state(s) to be bolstered via

cross-subsidization by a relatively high performing state. Manipur and Tripura are both relatively poor performing states and hence their grouping into a joint cadre doesn't provide much gain. 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.

Thus 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 the combining new states with their mother states; however, whether or not certain groupings would be politically viable is beyond the scope of this paper. Finally, 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.

6.3. Nudging Candidates' 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 good and which are bad. Should the government deem it fit, these preferences can be nudged either explicitly or implicitly.

The government can explicitly mandate restrictions over how candidates are allowed to order their preferences over state cadres. For example, if candidates are forced to include at least 1 of the bad cadres in every 3 choices, this correlation can be broken. We show in Figure 31 how such reservations can help improve uniformity in exam ranks. The reserve-3 green curve represents running a mechanism where candidates state their preferences and the mechanism runs through candidates in order of exam ranks and matches based on available vacancies. We see that such a preference restriction policy—though not as good in terms of balance as the simulated Old Mechanism or mechanism assuming uncorrelated preference—is a significant improvement over simulations assuming block preferences (randomly ordered block of good cadres followed by randomly ordered block of bad cadres), close-distance preferences (distance from home state), and the New Mechanism⁴⁹.

On the other hand, implicit nudges can be structured in various ways. Firstly, IAS officers working in distressed areas can be compensated with an income bonus, better facilities, and increased perks⁵⁰. 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 center 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. Lastly, to address the paucity of toppers from bad cadres, the government can establish civil service training centers, reserved

⁴⁹In all these simulations we assume that the candidates rank their home state (insider state) as their top preference, and the rest of the preferences are adjusted accordingly.

⁵⁰See 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.

seats⁵¹, or relaxed qualification requirements for candidates from bad cadres⁵². It is debatable whether such moves are politically feasible, but our purpose is simply to illustrate various points of attack to alleviate the distributional asymmetries prevalent in the system.

7. TWO-SIDED CADRE ALLOCATION MECHANISMS

Duties of the IAS include a) maintaining law and order (serving as the executive magistrate), b) revenue administration (collection of revenue, acting as courts in revenue matters, and supervising expenditure of public funds), and c) general administration (serving development officers, implementing policies, and formulating policies). Their positions can range 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 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. Ferguson and Hasan (2013) show that specialization and skill acquisition is beneficial for IAS officer's career trajectory throughout his or her career. Early on in the career, specialization signals general ability and helps promotion to the Centre posting, and later on in the career, specialization boosts likelihood of empanelment where the posting is likely to match the field of specialization. Hjort et al. (2015) find that education and local language proficiency predict high value-added officers. Hence, education, specialization, and being able to speak the local language seem to predict bureaucratic success both in terms of higher likelihood of promotion and better outcome performance.

IAS officers have diverse education backgrounds ranging from medical doctors and MBAs to engineers and economics PhDs. Thus, it seems like there is value added from having cadres express preferences over candidates based on the skills their vacancies require. Furthermore, 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 incorporating cadre preferences over candidates, the matching becomes two-sided.

⁵¹For 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.

⁵²For 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.

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 first dimension being mother tongue matching local language spoken (in order of popularity) and 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. 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. (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. Moreover, the cadre-proposing mechanism produces a narrower range of t-statistics across the various assumptions for candidate preferences. On the other hand, with candidate-proposing mechanism, the Uncorr and Res 3 preferences for the most part dominate the Block and Close preferences as for quality distribution imbalance.

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. Despite truncation of preferences (i.e., a cadre declaring that a candidate is unacceptable or a candidate declaring that a cadre is unacceptable) being prohibited by design⁵³, the candidate-proposing mechanism is non-strategyproof for cadres and cadre-proposing mechanism is non-strategyproof for candidates. We see in Figure 36 that which side proposes affects the performance in terms of average rank in preference of allotted match. 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 performs better than the New Mechanism (but slightly worse than the Old Mechanism) in terms of quality uniformity. Importantly, the upside from matching more bureaucrats with local language proficiency can be large.

7.1. Implementation of Reservations via Soft Constraints.

The two-sided simulations so 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

⁵³Truncated preferences are assumed to indicate indifference over unranked cadres. Hence, no match can be declared unacceptable.

balance constraints and Rural Hospital problem. Instead, we are faced with incorporating the reservations for quota candidates and insider candidates. Incorporating affirmative action policies in matching markets is an active area of research (see Section 3). Since candidates belonging 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—initial rosters of vacancies and candidates — implies that implementation with hard constraints will necessarily be wasteful. Moreover, Kojima (2012) shows how hard constraints such as upper-bounds on non-affirmative action seats suggested by Abdulkadiroglu and Sonmez (2003), can make affirmative action candidates worse off. Thus, instead of using hard constraints, we use the literature initiated by Hafalir et al. (2013) on implementing quotas with soft constraints: setting reserves for quota candidates, where until the reserve is filled in each state, quota candidates are given priority over non-quota candidates.

We implement our reservation policies using Deferred Acceptance with soft constraints. 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. Hence, no candidate is deemed unacceptable for reservation reasons and this ensures a non-wasteful match.

First we allow reservation only for insiders (Figures 37 and 38), then we allow reservation only for quotas SC/ST category and OBC category (Figures 39 and 40), and finally we allow reservation by quota x insider (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 categories⁵⁴. By making all candidates apply first to the non-reserved seats and then to the reserved seats, we allow for the possibility that some reservation candidates qualify for non-reservation seats, leading to weakly less competition for the remaining reservation candidates for their reservation category’s priority seats. Hence, when imposing reservations for insiders, we make all candidates prefer non-priority seats before insider-priority seats. When imposing reservations for SC/ST and OBC, we make all candidates prefer non-priority seats, followed by OBC priority seats, and then SC/ST priority seats. Similarly, when imposing quota x insider reservations, 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,

⁵⁴We thank Ignacio Rios for sharing this insight from his work in progress.

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.

These matchings will be stable under 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. We need to weaken the standard notion of stability to accommodate two-sided matching with constraints, and because we have overlapping dimensions in our reservation dimensions, we need the roster of vacancies to specify vacancies for each particular group: (embeddedness \times quota). Justified envy is imperative to ignore envy for vacancies in which the candidate has a lower priority. The roster of vacancies by embeddedness \times quota is crucial for stability, otherwise, candidates who qualify for multiple reservation types (for example, insider and OBC), can be allotted to priority seat in one dimension (say insider), but be envious of priority seat in the other dimension (OBC priority seat).

7.2. 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)⁵⁵. Firstly, similar to simulations in Celik (2014), the more correlated candidate's preferences are, the worse off they are, particularly when they propose, as increased competition amongst candidates for highly sought-after positions leads to a lot of rejections⁵⁶. 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 correlated⁵⁷. 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 expect that if we consider preferences by expertise, cadre's preferences over candidates might be even less correlated. 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, it seems that 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

⁵⁵It 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 over varying intensities of improvements. Deferred Acceptance produces the optimal stable matching for the proposing side; we graph aggregates for simplicity.

⁵⁶See Knuth (1997) and Caldarelli and Copocci (2001) for comments and simulations regarding Deferred Acceptance with correlated preferences.

⁵⁷Such statements on welfare are made strictly from an ordinal (and not cardinal) utility standpoint.

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 have the more correlated side break ties is an interesting question to pursue in future research⁵⁸.

Such an emphasis on correlation of preferences arises in this political economy application, because the mechanism designer—the Indian central government—has global uniformity considerations across cadres. In most matching applications such as school choice, the underlying preferences are taken as given and market-driven allocations aren’t restrained with cross-group equalizing constraints such as constraints on making the schools equally content with their allotted students or imposing that all schools be of a comparable student quality.

7.3. 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. If there are more candidates willing to be insiders then there are insider vacancies overall, who is allocated to their home cadre depends on which quota category is given more vacancies. Similar effects occur in two-sided matching with soft constraints. 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 vacancies⁵⁹. However, to the extent SC, ST, and OBC candidates tend to have lower exam ranks, this will affect quality of assigned candidates. Hence, by shifting vacancies within a state, the quality of assigned candidates and the distribution of quality across cadres changes, and states can prioritize certain quota groups in getting in by increasing the number of vacancies in that insider quota group. However, this power can be misused. 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 onwards with the New Mechanism, cadre vacancies are made available prior to the list of candidates, so this point of contention has become moot. Adjusting vacancies ex-post may be construed as unfair, but from a matching theory perspective, it is important to bring to attention.

⁵⁸The probabilistic claim in the extreme case of a market with one side having perfectly correlated preferences (such as all cadres having preferences over candidates in order of exam rank) and other side having completely uncorrelated preferences is intuitive. We expect, this intuition generalizes to non-extreme cases of relative correlations.

⁵⁹In the Old Mechanism, swaps require corresponding outsider vacancies in the quota category.

In constructing the final list of qualified candidates to match the number of vacancies, the UPSC has chosen to prioritize exam rank and quota, and not embeddedness (i.e., insiders). 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 categories⁶⁰. There are always weakly more SC, ST, and OBC candidates than 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. Hence, the shortcoming faced by bad cadres in placing insiders can be relaxed at the cost of lower exam ranks, if the UPSC goes further down the exam rank of candidates to get toppers from home states which aren't represented in the current lists. In light of Bhavnani and Lee (2016), Vaishnav and Khosla (2016) have 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 cost of making the insider constraints hard, is admitting candidates with lower exam rank.

8. EXTENSIONS TO OTHER CIVIL SERVICES & MATCHING APPLICATIONS

Our analysis can be immediately extended to the other two All-India Services—Indian Police Service (IPS) and Indian Forest Service (IFoS)—which share the same mechanisms we analyzed above. Although data availability is scarce, we show in Appendix C that analogous imbalances on the quality dimension with the New Mechanism arise in the IPS and IFoS (see Figure 46). 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 (see Tables 21 and 23). This data further corroborates our assumptions of a near unanimous preference for being an insider (i.e., first choice as home cadre) and shows that a vast majority over 90% of candidates give complete rank order preferences (see Table 22).

The relevance of 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, and thus the accompanying concerns of quality balance naturally arise. Furthermore, affirmative action policies and regional representation are also universal concerns 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 and post (i.e., Chinese bureaucracy), 2) appointment to a particular service and post (i.e., US President appoints and Congress must approve senior civil servants for government agencies), 3) centralized, synchronous assignment of many bureaucrats to posts (i.e., annual cadre allocation of IAS officers), and 4) centralized, dynamic assignment of civil servants (i.e., US Foreign Service where transfers and promotions are made dynamically as openings arrive). The first two categories are more aligned with decentralized, labor market models involving search. Matching theory, along the lines of school choice or residency matching, plays a key role in centralized, synchronous assignment as we see in this paper. Finally, matching theory

⁶⁰There are also various other special considerations for disabled candidates which we omit in this procedural overview.

similar to the dynamic kidney exchange markets, can be used to address the fourth category of civil service allocation systems. This is a promising avenue for future research.

Lastly, the novel constraint for quality balance that we identify in this paper, is more general than just the bureaucracy application. For example, matching problems in the military may require uniformity of talent across various battalions or divisions⁶¹, and in matching public school teachers to schools, the government may want to make different schools and school districts roughly comparable in teacher quality⁶². Understanding such constraints and designing mechanisms to address the underlying correlations in the data is also a promising area for future work.

9. CONCLUSION

We believe that approaching certain assignment problems in political economy from a matching theory framework can be a productive enterprise. In this paper, we study the impact of various matching mechanisms for the initial assignment of top-level Indian civil servants to state cadres. As a central planner and a mechanism designer with a social welfare function, the government often wants to impose constraints, such as uniformity of quality across state cadres along with balance on overlapping dimensions like quota and embeddedness, the likes of which don't necessarily arise in canonical, more market-driven matching or market design applications. Such constraints can highlight the importance of 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 in most matching applications. However, systematic imbalances—such as those resulting from the New Mechanism—further exacerbated by these correlations in covariates, 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 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, 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 central government to decide how to resolve these trade-offs and optimize given their desired weights on the constraints and outcomes.

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⁶¹For example, 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.

⁶²For example, Sonmez (2013) studies the matching of cadets to various divisions of the military. Matching mechanisms to assign teachers to schools have been used in countries like France (Terrier (2014)).

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Results shown in most Tables and Figures show analysis based on data 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 1. Effect of New Mechanism on Average Exam Rank and Normalized State Average Exam Rank, using data from 2005-2013.

$Y = \alpha + \beta \mathbb{1}_{BadCadre} * \mathbb{1}_{NewMechYears} * t + \eta_s + \tau_t$ for Average Exam Rank and Normalized State Average Exam Rank. Normalized State Average Exam Rank is $\frac{\mu_c - \mu}{\sigma}$ where μ_s is state cadre c 's average exam rank of assigned candidates, $\mu = \text{mean}(\mu_c)$ is the average exam rank across states and $\sigma = \text{stddev}(\mu_c)$. We see that from 2008 onwards, with the New Mechanism, the good and bad cadres diverged in quality of assigned candidates. See Table 24 for year-by-year effects and placebo tests.

	(1)	(2)
	StAvgExmRnk	NormalizedStExmRnk
badcadrenewmech	114.8*** (24.56)	0.784*** (0.202)
Constant	72.99*** (9.514)	-0.153*** (0.0925)
Year FE	✓	✓
State FE	✓	✓
Observations	216	216

Standard errors in parentheses are clustered at the state cadre level

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

Table 2. Ratio of Toppers/Vacancies and Average Exam Rank.

Correlation between a cadre's ratio of toppers to total vacancies and average exam rank of assigned IAS officers. There is a small negative correlation with the Old Mechanism (2005-2007), but large negative correlations with the New Mechanism (2008 onwards).

Years	Correlation
2005-07	-0.03
2008-13	-0.55
2014-15	-0.35

Table 3. Summary statistics for variables used in discrete choice analysis of preferences (in Tables 4 and 5).

Variable	Mean	Std Dev	Min	Max
DistanceFromHomeStMiles	697.0949	380.7953	0	1637
GSDP Per Capita	28906.81	9726.827	8621	49385
Health Index	.5988333	.0999352	.417	.817
PercentageRuralRoadsSurfaced	.6694847	.2169275	.1226844	.989721

Table 4. Discrete Choice Analysis of Cadre Preferences

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. Column (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) DistancefromHomeStMiles is the distance in miles between capital cities of the home cadre and ranked cadre. ii) GSDPPERcapita is the gross state domestic product per capita from year 2004-2005. iii) Health Index is the health index for 2008 computed in forming the Human Development Index from the India Human Development Report 2011. iv) PercentageRuralRoadsSurfaced is the percentage of rural roads which are surfaced from data.gov.in. v) InsiderState is an indicator variable if the ranked cadre is the candidate's home cadre. vi) Distance squared is the square of distance from home state in miles.

	(1) Cond logit	(2) Cond logit	(3) Rk-ordered logit	(4) Rk-ordered logit	(5) Lin regression
	PrefRank_Top5	PrefRank_Bottom5	PrefRank	PrefRank	PrefRank
DistancefromHomeStMiles	-0.00409*** (0.000354)	0.00194*** (0.000246)	-0.00131*** (0.000125)	-0.000673** (0.000270)	-0.00649*** (0.000313)
GSDPPERcapita04-05	0.0000320*** (0.0000122)	-0.00000526 (0.00000705)	0.0000108*** (0.00000370)	0.0000107*** (0.00000367)	0.0000533*** (0.0000194)
HealthIndex08	1.316 (0.922)	-2.331*** (0.813)	1.359*** (0.339)	1.543*** (0.355)	7.188*** (1.841)
PercentageRuralRoadsSurfaced	1.771*** (0.376)	-3.128*** (0.253)	1.555*** (0.105)	1.537*** (0.106)	9.425*** (0.598)
distancesquared				-0.000000447** (0.000000179)	
Constant					4.897*** (0.961)
Observations	2783	2622	2806	2806	2806
R^2					0.277
log likelihood	-799.50	-982.087	-6020.5567	-6018.765	
log likelihood (intercept only)	-1105.08	-1182.97			

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 Preferences

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. In the last row, the effect of ranked cadre being the candidate's home cadre is shown as a factor of 1 standard deviation effect of distance from home state in miles.

	(1)	(2)	(3)
	Cond logit	Cond logit	Rk-ordered logit
	PrefRank_Top5	PrefRank_Bottom5	PrefRank
DistancefromHomeStMiles	1	1	1
GSDPPercapita2004-05	5.00	14.43	4.74
HealthIndex2008	11.84	3.17	3.67
PercentageRuralRoadsSurfaced	4.05	1.09	1.48

Table 6. Relative Effect Sizes in Cadre Preferences in terms of Distance from Home State in Miles

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

	(1)	(2)	(3)
	Cond logit	Cond logit	Rk-ordered logit
	PrefRank_Top5	PrefRank_Bottom5	PrefRank
DistancefromHomeStMiles	381	381	381
GSDPPercapita2004-05	76	26	80
HealthIndex2008	32	120	103
PercentageRuralRoadsSurfaced	94	350	257

Table 7. Distance Willing to Travel for Each Cadre Relative to Average Cadre
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 most of the bad cadres appear at the very bottom of the list.

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

Table 8. Exam Toppers from Cadres

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.

	(1) Poisson Reg	(2) Poisson Reg	(3) Poisson Reg
	NumberToppers	NumberToppers	NumberToppers
HealthIndex08	5.943*** (0.823)	4.773*** (0.848)	3.733*** (0.905)
PerCapitaIncome2011-12	0.00000977*** (0.00000244)	0.00000697*** (0.00000229)	0.00000576*** (0.00000222)
Population_Census2011	1.52e-08*** (6.80e-10)	1.76e-08*** (1.08e-09)	1.38e-08*** (7.03e-10)
LiteracyRate2011Census	-0.0875*** (0.0125)		
LiteracyRateRural2011		-0.0363** (0.0163)	
LiteracyRateUrban2011		-0.0437** (0.0202)	
EducationIndex2008			-2.298** (0.922)
Constant	2.610*** (0.906)	3.025*** (1.096)	-0.881** (0.436)
Year Fixed Effects	✓	✓	✓
Observations	216	216	216

Standard errors in parentheses

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

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

We use state-level revenue data from 12th and 13th Finance Commission Reports covering fiscal years 2005 to 2015 to estimate $Y = \alpha + \eta_s + \gamma_s * t + \beta \mathbb{1}_{BadCadre} * \mathbb{1}_{NewMechYears} * t + \tau_t + \epsilon$. 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 22 difference-in-difference graphs, and for robustness on non-tax revenue regressions see Figure 23 and Table 12.

	(1)	(2)
	Own Tax Revenue	Non-Tax Revenue
badcadrenewmech \times lineartrend	-1336.6** (641.5)	-111.0 (100.6)
badcadrenewmech	5361.9 (4136.3)	-352.6 (356.4)
lineartrend	6779.3*** (19.94)	594.5*** (23.69)
Constant	8246.3*** (614.7)	3122.7*** (215.9)
Year FE	✓	✓
State FE	✓	✓
State Linear Time Trend	✓	✓
Observations	280	280

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.

We use state-level revenue data from 12th and 13th Finance Commission Reports covering fiscal years 2008-2015 (IAS batches 2005-2013) to estimate reduced form $Y = \alpha + \beta X + \eta_s + \tau_t + \epsilon$ for Average Exam Rank and Normalized State Average Exam Rank. IV estimates instrument for X using first stage $\hat{X} = \alpha + \beta \mathbb{1}_{BadCadre} * \mathbb{1}_{NewMechYears} * t + \eta_s + \tau_t$.

	(1) Reduced Form	(2) IV_DiD	(3) Reduced Form	(4) IV_DiD
StAvgExmRnk	-20.11*** (7.158)	-85.11*** (23.71)		
NormalizedStExmRnk			-2492.8*** (820.4)	-11909.6*** (3338.6)
Constant	41759.0*** (1651.8)	69129.0*** (4917.0)	39934.6*** (2037.8)	54332.8*** (1798.8)
Year FE	✓	✓	✓	✓
State FE	✓	✓	✓	✓
Observations	224	224	224	224

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.

We use state-level revenue data from 12th and 13th Finance Commission Reports covering fiscal years 2005 to 2015 (IAS batches 2005-2013). We de-trend each state using its own Old Mechanism (2005-2010) trend, and then estimate difference-in-difference on the de-trended data: $Y = \alpha + \beta \mathbb{1}_{BadCadre} * \mathbb{1}_{NewMechYears} + \eta_s + \tau_t + \epsilon$, 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 atleast an order of magnitude smaller than the New Mechanism effects. The effect on non-tax revenues (*Columns (4) -(6)*) for New Mechanism years (2010-15) 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 difference-in-difference graphs, and for robustness on non-tax revenue regressions see Figure 25 and Table 12.

	(1)	(2)	(3)	(4)	(5)	(6)
	DetOwnTaxRev	DetOwnTaxRev	DetOwnTaxRev	DetNonTaxRev	DetNonTaxRev	DetNonTaxRev
badcadrenewmech	-5330.9*** (1632.9)			-1240.4 (794.6)		
bad15		-8365.9*** (2785.1)	-8194.1*** (2746.9)		-1509.4 (984.8)	-1481.6 (994.9)
bad14		-6472.8*** (2044.9)	-6301.0*** (2011.3)		-1279.4 (889.9)	-1251.7 (898.9)
bad13		-4984.9*** (1553.5)	-4813.1*** (1533.8)		-1234.3 (796.2)	-1206.5 (804.6)
bad12		-3822.9*** (1284.2)	-3651.1*** (1285.6)		-1169.0 (714.2)	-1141.3 (721.7)
bad11		-3007.9** (1171.8)	-2836.1** (1192.5)		-1009.7 (641.1)	-981.9 (647.4)
bad10			-9.654* (5.013)			-1.304 (1.607)
bad09			271.4** (126.7)			43.09** (17.68)
bad08			345.3** (162.9)			56.57*** (21.69)
bad07			252.1** (116.7)			40.48*** (15.17)
Constant	26510.5*** (743.2)	26510.5*** (749.4)	26565.7*** (740.3)	2373.1*** (375.3)	2373.1*** (378.5)	2382.0*** (381.6)
Year FE	✓	✓	✓	✓	✓	✓
State FE	✓	✓	✓	✓	✓	✓
Observations	280	280	280	280	280	280

Standard errors in parentheses are clustered at the state cadre level

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

Table 12. Non-Tax Revenue Robustness (incl. and excl. Maharashtra & Haryana)

Since Haryana and Maharashtra cause the seeming jump in the non-tax revenues (see Figures 23 and 25), 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.

	excl. Maharashtra and Haryana		excl. Maharashtra		excl. Haryana	
	(1)	(2)	(3)	(4)	(5)	(6)
	DetNonTax	Non-Tax	DetNonTax	Non-Tax	DetNonTax	Non-Tax
badcadrenewmech	-349.2 (385.9)	-70.81 (228.1)	-1006.0 (792.6)	-96.42 (218.0)	-633.0 (480.5)	-342.6 (375.9)
badcadrenewmech \times lineartrend		-34.80 (58.73)		-113.7 (105.7)		-36.30 (56.54)
lineartrend		622.2*** (9.433)		604.3*** (22.12)		610.9*** (15.66)
Constant	2816.7*** (143.2)	2889.5*** (85.80)	2488.5*** (374.7)	3070.1*** (219.4)	2676.6*** (201.4)	2955.1*** (109.6)
Year FE	✓	✓	✓	✓	✓	✓
State FE	✓	✓	✓	✓	✓	✓
State Linear Time Trend		✓		✓		✓
Observations	260	260	270	270	270	270

Standard errors in parentheses are clustered at the state cadre level

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

Table 13. Forgone Own Tax Revenue due to Reservation Policies (Counterfactual).

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 $65 \frac{INR}{USD}$.

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

Table 14. Forgone Own Tax Revenue due to ST Reservation Policies (Counterfactual).

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 $65 \frac{INR}{USD}$.

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

Table 15. Forgone Own Tax Revenue due to SC Reservation Policies (Counterfactual).

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 $\frac{INR}{USD}$.

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

Table 16. Forgone Own Tax Revenue due to OBC Reservation Policies (Counterfactual).

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 $\frac{INR}{USD}$.

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

Table 17. Difference in difference effect of New Mechanism on Human Development Index (HDI). Data used is HDI for years 1983, 1988, 1993, 2000, 2005, 2010, and 2012 constructed by Mukherjee et. al (2014).

	(1) HDI
badcadrenewmech	-.0488** (.0224)
Constant	.2598*** (.0143)
Year FE	✓
State FE	✓
Observations	196
Standard errors in parentheses	
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$	

Table 18. Effect of New Mechanism on Age of Candidates.

Regressing $AverageAge = \alpha + \beta_1 \mathbb{1}_{BadCadre} * \mathbb{1}_{NewMechYears} + \eta_s + \tau_t + \epsilon$. 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)).

	(1) Age	(2) Age
$\mathbb{1}_{BadCadre} * \mathbb{1}_{NewMechYears}$	0.466* (0.273)	0.396 (0.269)
Constant	24.45*** (0.348)	24.45*** (0.360)
Year FE	✓	✓
State FE	✓	✓
Observations	662	684
Number of cadres	23	24
Standard errors in parentheses		
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$		

Table 19. Recruitment practices under Old and New Mechanisms.

$Y = \alpha + \beta_1 \mathbb{1}_{BadCadre} + \beta_2 \mathbb{1}_{NewMechYears} + \beta_3 \mathbb{1}_{BadCadre} * \mathbb{1}_{NewMechYears} + \epsilon$. The dependent variables are Percentage of IAS officers who are promoted from State Civil Service (*Column 1*), Percentage of IAS officers who are promoted from State Civil Service relative to authorized strength (*Column 2*), and Percentage of IAS officers who are Direct Recruits relative to authorized strength (*Column 3*). This data is from Civil Lists 2001-2017.

	(1) %PromotedActual	(2) %PromotedtoStrength	(3) %DirecttoStrength
$\mathbb{1}_{BadCadre}$	0.0746*** (0.00976)	0.0821*** (0.0294)	-0.156*** (0.0155)
$\mathbb{1}_{NewMechYears}$	0.00884 (0.00685)	-0.115*** (0.0206)	-0.195*** (0.0109)
$\mathbb{1}_{BadCadre} * \mathbb{1}_{NewMechYears}$	-0.0261** (0.0126)	-0.0257 (0.0380)	0.105*** (0.0200)
Constant	0.247*** (0.00527)	0.775*** (0.0159)	1.014*** (0.00837)
Observations	415	415	415
R-squared	0.189	0.133	0.520

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 20. Ratio of Toppers relative to Vacancies for new states formed in 2000.

The low ratio of 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.

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

Figure 4. Average exam rank differences between assigned insiders and outsiders by category. Analysis separated into years 2005-07 (Old Mechanism), 2008-13 (New Mechanism), and 2014-15 (New Mechanism with new states).

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

Figure 5. Average exam rank of assigned candidates by cadre. Highlighted entries show the impact of some cadres splitting up in 2014. Analysis separated into years 2005-07 (Old Mechanism), 2008-13 (New Mechanism), and 2014-15 (New Mechanism with new states).

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

Figure 6. Variance of within-cadre average exam rank across all cadres. Notice the increases in variance with the New Mechanism (2008 onwards) and with the formation of new states in 2014.

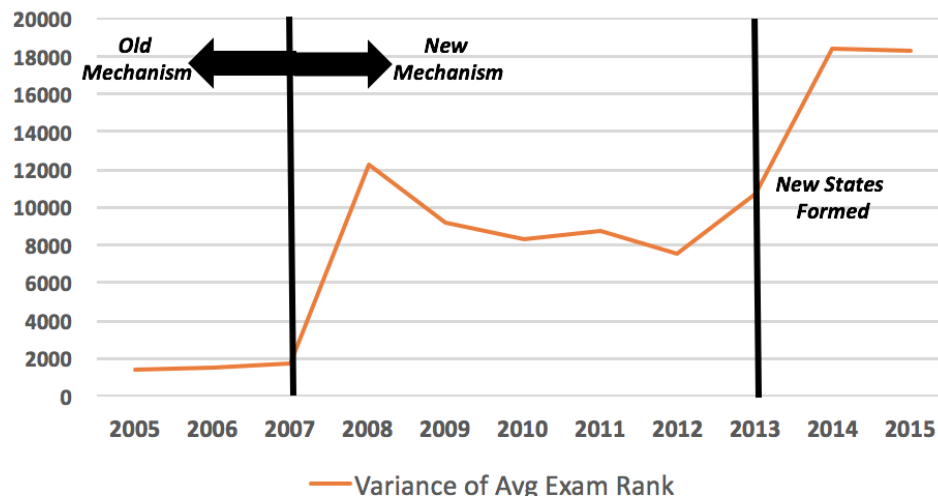


Figure 7. Average exam rank of assigned candidates by reservation. Analysis separated into years 2005-07 (Old Mechanism) and 2008-13 (New Mechanism).

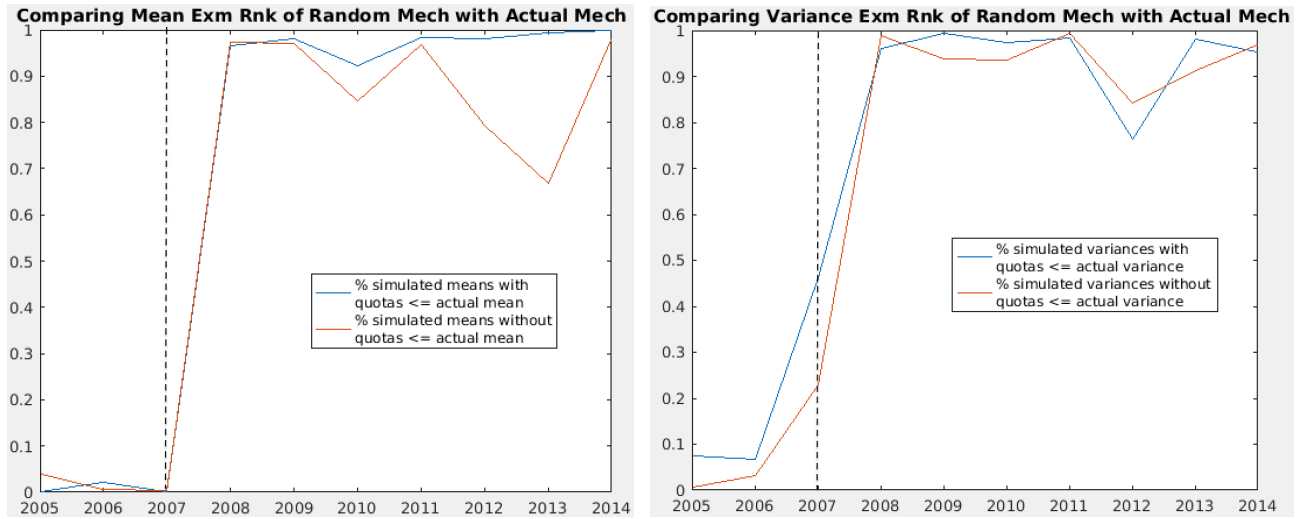
2005-2007				2008-2013				2014-2015			
State	General State		O.B.C.	State	General State		O.B.C.	State	General State		O.B.C.
Haryana	12	Himachal Pra	43	Rajasthan	17	Karnataka	78	Haryana	3	Rajasthan	106
Kerala	17	Maharashtra	52	Punjab	18	Andhra Prade	84	Rajasthan	13	Tamil Nadu	142
Punjab	17	Andhra Prade	53	Haryana	18	Rajasthan	88	Punjab	21	Andhra Prade	142
Nagaland	21	Bihar	53	Gujarat	30	Tamil Nadu	90	Gujarat	29	Karnataka	165
Orissa	22	Nagaland	54	Madhya Pra	34	Maharashtra	100	Maharashtra	29	Punjab	168
Sikkim	22	Haryana	62	Karnataka	38	Haryana	104	Madhya Prac	33	A G M U T	178
Andhra Prade	24	Assam Megh	66	Himachal Pi	39	Uttar Pradesi	107	Andhra Prade	37	Bihar	198
Uttarakhand	24	Orissa	67	Tamil Nadu	39	Punjab	110	Uttar Pradesi	39	Madhya Prac	203
Jharkhand	26	Rajasthan	68	Uttarakhan	39	Uttarakhand	121	Karnataka	40	Orissa	206
Assam Megh	26	Karnataka	69	A G M U T	44	Kerala	122	Himachal Pra	45	Uttarakhand	206
Maharashtra	32	Punjab	69	Maharashtr	45	Bihar	126	Jharkhand	49	Haryana	220
Rajasthan	33	Manipur Trip	70	Andhra Prai	50	A G M U T	130	Telangana	50	Maharashtra	226
Manipur Trip	33	Tamil Nadu	70	Bihar	53	Madhya Prac	133	Bihar	54	Gujarat	263
Chhattisgarh	35	Jharkhand	79	Orissa	59	Gujarat	135	A G M U T	54	Kerala	276
Gujarat	36	Sikkim	79	Uttar Prade	63	Jharkhand	149	Orissa	59	Jharkhand	308
Bihar	38	Madhya Prac	81	Jharkhand	71	Himachal Pra	151	Tamil Nadu	60	Himachal Pra	313
A G M U T	38	A G M U T	88	Sikkim	88	Orissa	153	Kerala	62	Telangana	335
Jammu & Kas	39	West Bengal	89	Kerala	101	Chhattisgarh	162	Chhattisgarh	66	Chhattisgarh	357
Tamil Nadu	42	Chhattisgarh	93	West Benga	120	Sikkim	179	West Bengal	80	Uttar Pradesi	371
Madhya Prac	61	Uttarakhand	97	Chhattisgar	140	West Bengal	194	Jammu & Kas	147	West Bengal	390
West Bengal	97	Kerala	97	Jammu & K:	149	Assam Megh	226	Manipur	181	Jammu & Kas	400
Karnataka	114	Uttar Pradesi	100	Assam Meg	227	Jammu & Kas	258	Assam Megh	219	Sikkim	425
Uttar Pradesi	142	Gujarat	231	Manipur Tri	391	Manipur Trip	265	Uttarakhand	328	Tripura	426
Himachal Pradesh	Jammu & Kashmir			Nagaland	Nagaland		291	Tripura	502	Manipur	431
								Nagaland	Nagaland		530
								Sikkim	Assam Meghalaya		

2005-2007				2008-2013				2014-2015			
State	S.C.	State	S.T.	State	S.C.	State	S.T.	State	S.C.	State	S.T.
Sikkim	67	Tamil Nadu	29	Karnataka	108	Gujarat	59	A G M U T	134	Madhya Prac	224
Bihar	84	West Bengal	48	Maharashtr	154	Madhya Prac	228	Madhya Prac	225	Jammu & Kas	253
Assam Megh	117	Haryana	78	Haryana	164	Assam Megh	239	Karnataka	274	Haryana	280
Rajasthan	120	Gujarat	113	Jammu & K:	167	Andhra Prade	240	Gujarat	283	Punjab	401
Karnataka	125	Assam Megh	125	Madhya Pra	186	A G M U T	243	Himachal Pra	312	Tamil Nadu	420
A G M U T	128	Andhra Prade	186	Kerala	199	Punjab	266	Andhra Prade	315	Uttar Pradesi	436
Himachal Pra	128	Manipur Trip	196	Tamil Nadu	200	Uttarakhand	313	Tamil Nadu	325	Telangana	528
Punjab	131	Punjab	223	Andhra Prai	217	Jammu & Kas	353	Telangana	379	Uttarakhand	547
Orissa	140	Jammu & Kas	228	Uttarakhan	229	Manipur Trip	361	West Bengal	398	A G M U T	550
Jammu & Kas	153	Nagaland	244	Gujarat	258	Orissa	369	Uttar Pradesi	409	Jharkhand	553
Uttar Pradesi	153	Bihar	245	Uttar Prade	264	Sikkim	371	Bihar	449	Karnataka	569
Uttarakhand	158	Madhya Prac	260	Orissa	274	Maharashtra	379	Haryana	468	Himachal Pra	612
Haryana	163	A G M U T	263	Sikkim	275	Himachal Pra	415	Chhattisgarh	477	Bihar	613
West Bengal	174	Uttar Pradesi	370	Punjab	280	Nagaland	451	Punjab	497	Chhattisgarh	764
Jharkhand	179	Chhattisgarh		A G M U T	289	Uttar Pradesi	452	Manipur	500	Assam Megh	773
Kerala	193	Himachal Pradesh		Jharkhand	302	Jharkhand	458	Kerala	503	Andhra Pradesh	
Nagaland	201	Jharkhand		Bihar	305	West Bengal	461	Jharkhand	515	Gujarat	
Madhya Prac	207	Karnataka		Chhattisgar	322	Kerala	463	Rajasthan	583	Kerala	
Maharashtra	210	Kerala		Nagaland	339	Rajasthan	475	Sikkim	595	Maharashtra	
Chhattisgarh	214	Maharashtra		Himachal Pi	344	Karnataka	567	Assam Megh	604	Manipur	
Gujarat	281	Orissa		Manipur Tri	362	Tamil Nadu	569	Nagaland	641	Tripura	
Tamil Nadu	285	Rajasthan		Rajasthan	364	Chhattisgarh	615	Orissa	650	Nagaland	
Andhra Pradesh		Sikkim		West Benga	377	Bihar	648	Jammu & Kashmir		Orissa	
Manipur Tripura		Uttarakhand		Assam Meg	378	Haryana		Maharashtra		Rajasthan	
								Tripura		Sikkim	
								Uttarakhand		West Bengal	

Figure 8. *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).

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 Pr.	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 Pradesh	0.33	Nagaland	0.13	Assam Megh	0.16
Rajasthan	0.30	Chhattisgarh	0.33	Manipur Trip	0.20	Gujarat	0.18
Uttar Pradesh	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 Pradesh	0.24
Assam Megh	0.33	Uttar Pradesh	0.33	Bihar	0.29	Orissa	0.24
Chhattisgarh	0.33	Uttarakhand	0.33	Madhya Pradesh	0.29	Jharkhand	0.26
Haryana	0.33	West Bengal	0.33	Maharashtra	0.29	Karnataka	0.28
Jammu & Ka	0.33	Madhya Pradesh	0.34	Rajasthan	0.30	A G M U T	0.29
Jharkhand	0.33	A G M U T	0.34	Uttar Pradesh	0.32	Punjab	0.31
Kerala	0.33	Maharashtra	0.34	A G M U T	0.33	Himachal Pradesh	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 Pradesh	0.33
West Bengal	0.33	Rajasthan	0.34	Jharkhand	0.33	Tamil Nadu	0.33
Madhya Pradesh	0.35	Haryana	0.35	Kerala	0.33	Uttar Pradesh	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 Pradesh	0.37	Orissa	0.38	Bihar	0.35
Andhra Pradesh	0.43	Sikkim	0.43	Andhra Pradesh	0.43	Kerala	0.35

Figure 9. 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.



Year	Haryana	Andhra Pradesh	Maharashtra	Manipur Tripura	Nagaland	Assam Meghalaya
2005	0.00	0.40	0.28	0.23	0.15	0.45
2006	0.75	0.15	0.27	0.25	0.65	0.38
2007	0.18	0.18	0.75	0.75	0.50	0.05
2008	0.38	0.03	0.52	1.00	0.40	0.50
2009	0.12	0.45	0.10	0.98	0.98	0.98
2010	0.02	0.02	0.45	0.95	1.00	0.90
2011	0.00	0.20	0.15	1.00	1.00	1.00
2012	0.00	0.15	0.38	1.00	1.00	1.00
2013	0.03	0.22	0.45	1.00	1.00	1.00



Figure 11. 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. We see that 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.



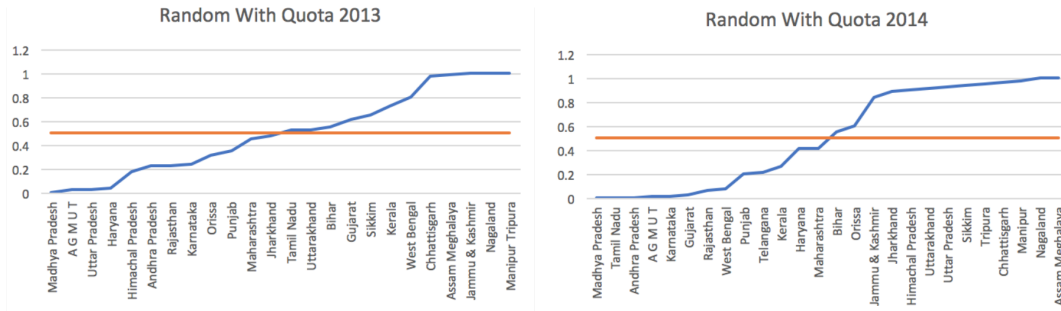


Figure 12. Estimated probability distribution function for exam toppers for selected cadres (using 2013 poisson regression coefficients for Uttar Pradesh ($\hat{\lambda} = 29.98$), Maharashtra ($\hat{\lambda} = 13.85$), Gujarat ($\hat{\lambda} = 6.95$), Jammu and Kashmir ($\hat{\lambda} = 3.29$), and Manipur Tripura ($\hat{\lambda} = 1.55$). We see a large heterogeneity in ability to place exam toppers across various cadres.

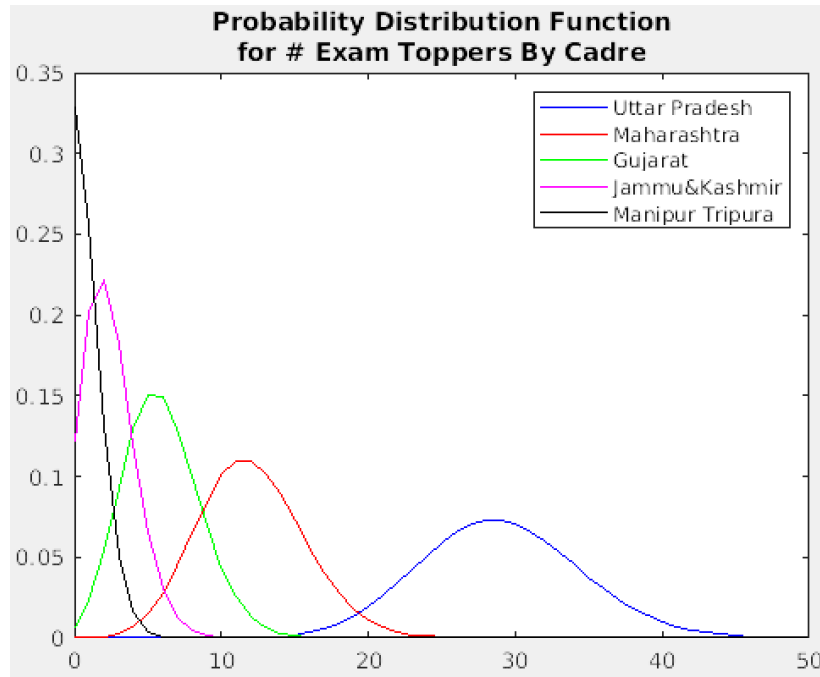


Figure 13. Average of within-cadre average exam rank (*left*) and Average of normalized state average exam rank (*right*), for Good (blue) and Bad (red) Cadres from 2005 to 2013. Normalized State Average Rank is $\frac{\mu_c - \mu}{\sigma}$ where μ_s is state cadre c 's average exam rank of assigned candidates, $\mu = \text{mean}(\mu_c)$ is the average exam rank across states, and $\sigma = \text{stddev}(\mu_c)$. We see that from 2008 onwards, with the New Mechanism, the good and bad cadres diverged in quality of assigned candidates.

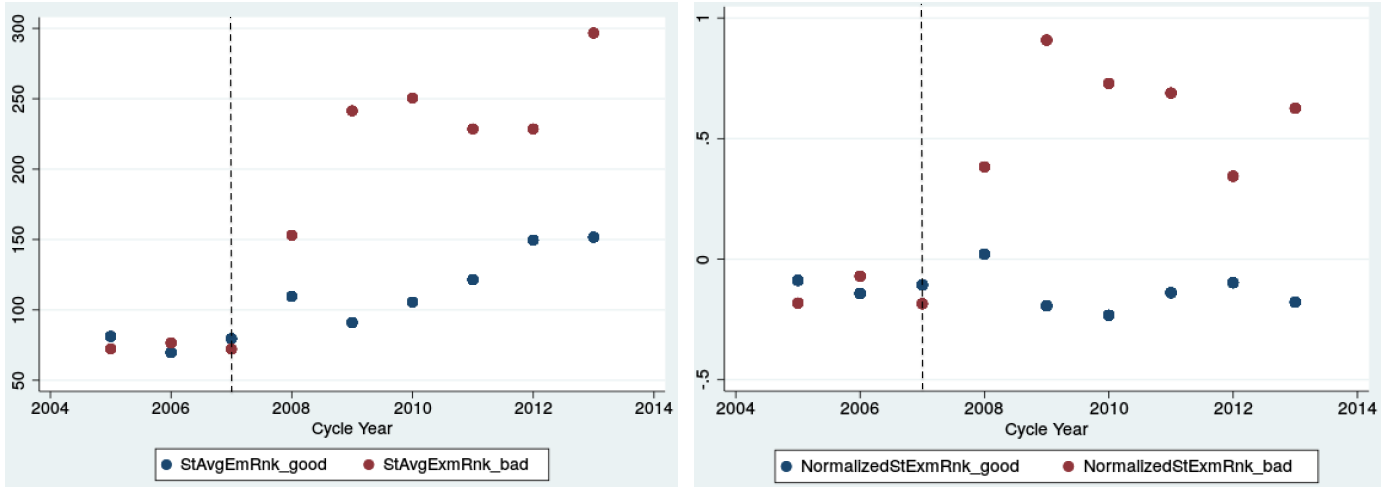


Figure 14. Ratio of exam toppers to total vacancies from each state. Analysis separated into years 2005-07 (Old Mechanism), 2008-13 (New Mechanism), and 2014-15 (New Mechanism with new states).

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

Figure 15. Average exam rank of candidates by Home State. Analysis separated into years 2005-07 (Old Mechanism), 2008-13 (New Mechanism), and 2014-15 (New Mechanism with new states).

2005-2007		2008-2013		2014-2015	
State	Rank	State	Rank	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	

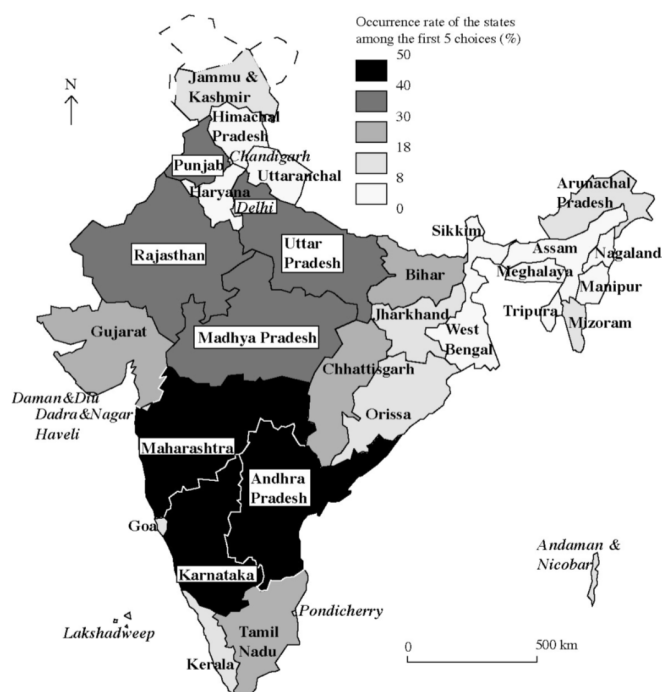
Figure 16. Average exam rank of candidates by Home State within each quota category. Analysis separated into years 2005-07 (Old Mechanism), 2008-13 (New Mechanism), and 2014-15 (New Mechanism with new states).

2005-2007				2008-2013				2014-2015			
State	Gen Rank	State	OBC Rank	State	Gen Rank	State	OBC Rank	State	Gen Rank	State	OBC Rank
Chhattisgarh	8.0	Andhra Pradesh	36.6	Jammu & Kashmir	27.5	Punjab	79.0	Jammu & Kashmir	2.0	Punjab	102.0
Andhra Pradesh	9.5	Chhattisgarh	38.0	Assam Meghalaya	28.3	Andhra Pradesh	107.2	Assam Meghalaya	16.0	Uttarakhand	145.0
Kerala	12.0	Haryana	38.0	Orissa	28.8	Tamil Nadu	112.5	Manipur	24.0	Manipur	167.0
Tamil Nadu	20.0	Rajasthan	55.7	Gujarat	32.0	Gujarat	124.0	Kerala	31.3	Haryana	171.4
Orissa	21.2	Kerala	58.3	Kerala	35.9	Bihar	127.3	Gujarat	40.0	A G M U T	179.3
Jharkhand	21.8	Jharkhand	65.3	West Bengal	38.0	Rajasthan	134.9	Bihar	41.4	Bihar	187.6
Punjab	24.7	Uttar Pradesh	69.4	Madhya Pradesh	38.3	Manipur Tripura	137.5	Orissa	41.8	Karnataka	213.3
West Bengal	24.8	Madhya Pradesh	76.0	Himachal Pradesh	41.5	Haryana	140.7	Himachal Pradesh	46.0	Andhra Pradesh	215.8
Haryana	28.9	Tamil Nadu	79.3	Uttarakhand	46.0	Chhattisgarh	145.0	West Bengal	46.3	Tamil Nadu	216.5
Rajasthan	29.1	Bihar	82.1	Punjab	46.0	Karnataka	147.7	Telangana	47.7	Jharkhand	228.5
Uttar Pradesh	36.1	Maharashtra	84.1	Andhra Pradesh	46.3	Uttar Pradesh	148.9	Jharkhand	53.3	Rajasthan	262.5
Maharashtra	40.1	Manipur Tripura	100.0	Karnataka	46.6	Kerala	159.6	Maharashtra	53.5	Chhattisgarh	279.0
Bihar	40.9	Karnataka	120.0	Manipur Tripura	47.0	Maharashtra	163.1	Madhya Pradesh	54.6	Kerala	287.1
Gujarat	41.0	A G M U T	126.7	Haryana	50.5	Orissa	178.7	Rajasthan	55.0	Gujarat	310.0
Madhya Pradesh	43.2	Assam Meghalaya		Chhattisgarh	53.9	Madhya Pradesh	184.7	A G M U T	56.1	Maharashtra	337.9
A G M U T	47.5	Gujarat		Tamil Nadu	58.5	Jharkhand	221.2	Sikkim	63.0	Telangana	341.3
Jammu & Kashmir	47.5	Himachal Pradesh		A G M U T	75.2	A G M U T	238.0	Punjab	64.6	Uttar Pradesh	392.1
Uttarakhand	52.5	Jammu & Kashmir		Uttar Pradesh	75.7	Assam Meghalaya	283.0	Uttar Pradesh	66.5	Assam Meghalaya	
Karnataka	200.0	Nagaland		Maharashtra	83.5	Himachal Pradesh		Haryana	66.8	Himachal Pradesh	
Assam Meghalaya		Orissa		Bihar	111.2	Jammu & Kashmir		Tamil Nadu	74.5	Jammu & Kashmir	
Himachal Pradesh		Punjab		Jharkhand	134.0	Nagaland		Andhra Pradesh	91.5	Madhya Pradesh	
Manipur Tripura		Sikkim		Rajasthan	170.6	Sikkim		Karnataka	149.5	Nagaland	
Nagaland		Uttarakhand		Nagaland		Uttarakhand		Uttarakhand	593.5	Orissa	
Sikkim		West Bengal		Sikkim		West Bengal		Chhattisgarh		Sikkim	
								Nagaland		Tripura	
								Tripura		West Bengal	

2005-2007				2008-2013				2014-2015			
State	S.C. Exm Rank	State	S.T. Rank	State	S.C. Rank	State	S.T. Rank	State	S.C. Rank	State	S.T. Rank
Orissa	101.5	Maharashtra	29.0	Uttarakhand	122.0	Gujarat	72.0	Madhya Pradesh	28.5	Madhya Pradesh	249.0
West Bengal	120.0	Himachal Pradesh	72.0	Jammu & Kashmir	145.0	Tamil Nadu	231.0	Karnataka	173.5	Andhra Pradesh	399.0
Karnataka	138.5	Gujarat	94.0	Madhya Pradesh	153.7	Manipur Tripura	256.3	A G M U T	197.9	Jammu & Kashmir	415.3
Uttar Pradesh	138.6	Assam Meghalaya	177.0	Chhattisgarh	155.0	Karnataka	258.0	Uttar Pradesh	362.6	Karnataka	462.3
Madhya Pradesh	142.7	Manipur Tripura	196.3	Haryana	170.7	Assam Meghalaya	298.3	Tamil Nadu	384.1	Rajasthan	490.6
Punjab	160.3	A G M U T	198.5	Manipur Tripura	236.0	Orissa	320.5	West Bengal	398.0	Telangana	534.0
Maharashtra	181.2	Rajasthan	199.7	Himachal Pradesh	240.7	Madhya Pradesh	351.0	Telangana	408.3	A G M U T	547.0
Jharkhand	182.0	Nagaland	244.0	A G M U T	243.8	Jammu & Kashmir	385.5	Maharashtra	465.8	Himachal Pradesh	611.5
Rajasthan	189.7	Karnataka	278.0	Andhra Pradesh	248.6	Andhra Pradesh	390.2	Haryana	468.0	Jharkhand	646.0
Tamil Nadu	205.1	Andhra Pradesh	297.5	Tamil Nadu	255.4	Rajasthan	407.8	Jammu & Kashmir	477.0	Assam Meghalaya	
A G M U T	214.5	Uttarakhand	326.0	Uttar Pradesh	266.8	A G M U T	465.5	Rajasthan	487.3	Bihar	
Andhra Pradesh	223.7	Bihar		Maharashtra	279.5	Sikkim	468.5	Andhra Pradesh	498.3	Chhattisgarh	
Assam Meghalaya		Chhattisgarh		Punjab	285.3	Himachal Pradesh	511.3	Manipur	500.0	Gujarat	
Bihar		Haryana		Karnataka	286.0	Maharashtra	528.0	Punjab	506.8	Haryana	
Chhattisgarh		Jammu & Kashmir		Kerala	297.5	Jharkhand	559.0	Orissa	650.0	Kerala	
Gujarat		Jharkhand		Rajasthan	316.6	Bihar		Assam Meghalaya		Maharashtra	
Haryana		Kerala		Bihar	325.0	Chhattisgarh		Bihar		Manipur	
Himachal Pradesh		Madhya Pradesh		West Bengal	326.0	Haryana		Chhattisgarh		Nagaland	
Jammu & Kashmir		Orissa		Gujarat	359.8	Kerala		Gujarat		Orissa	
Kerala		Punjab		Assam Meghalaya		Nagaland		Himachal Pradesh		Punjab	
Manipur Tripura		Sikkim		Jharkhand		Punjab		Jharkhand		Sikkim	
Nagaland		Tamil Nadu		Nagaland		Uttar Pradesh		Kerala		Tamil Nadu	
Sikkim		Uttar Pradesh		Orissa		Uttarakhand		Nagaland		Tripura	
Uttarakhand		West Bengal		Sikkim		West Bengal		Sikkim		Uttar Pradesh	
								Tripura		Uttarakhand	
								Uttarakhand		West Bengal	

Figure 17. 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.

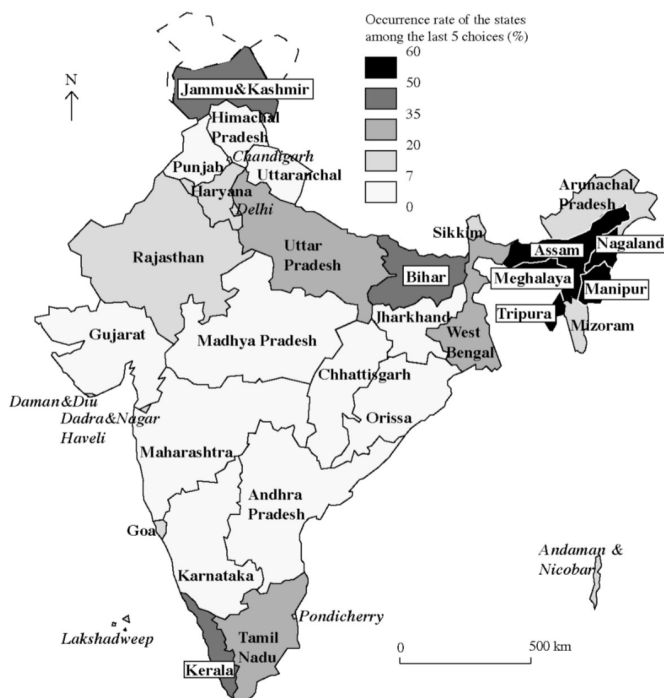
Figure 3 - Cadre preferences of IAS officers



(C) D. Benbabaali (2006)

Source : personal investigation

Figure 4 - Least preferred cadres among IAS officers



(C) D. Benbabaali (2006)

Source : personal investigation

Figure 18. Percentage of Homophily: Northerners assigned to Northern Cadres and Southerners assigned to Southern 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 under the New Mechanism.

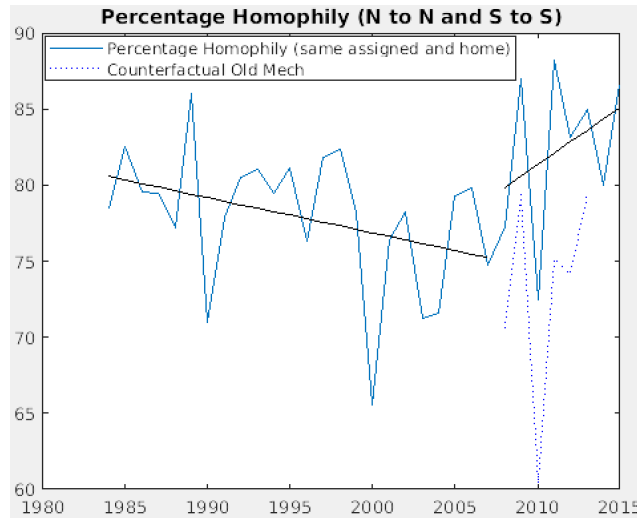


Figure 19. *Left:* Percentage of Southerners assigned to Southern Cadres. *Right:* Percentage of Northerners assigned to Northern Cadres. The solid blue line shows the actual assignment data, the dotted line is the simulated counterfactual using the Old Mechanism for years 2008 onwards, and the solid 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.

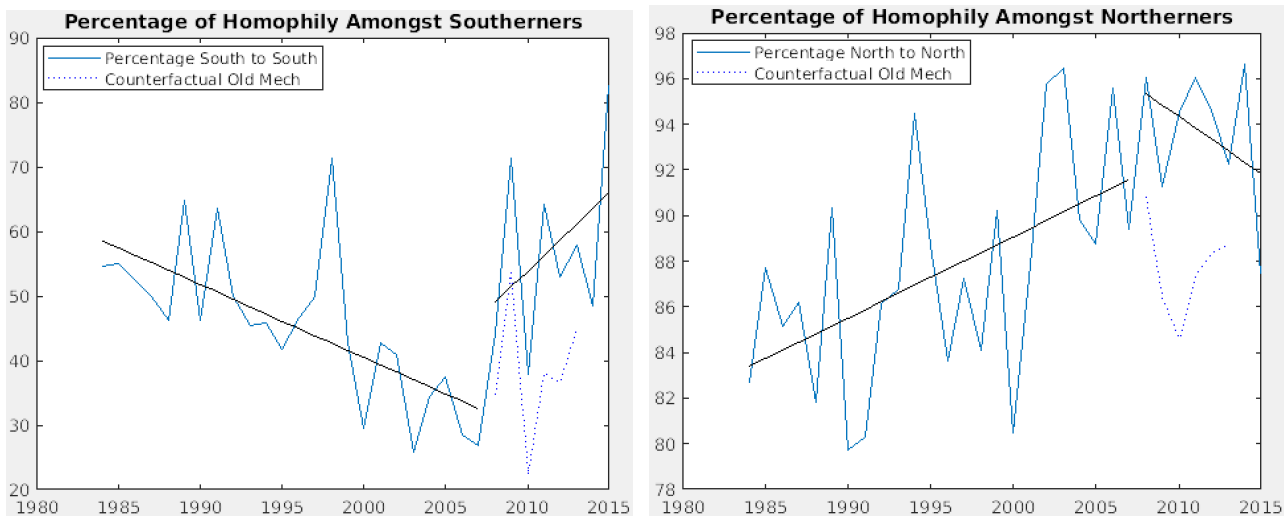


Figure 20. Mean (*Left*) and variance (*Right*) of distance from assigned cadre to home cadre across candidates by year. Distances are measured by miles between capitals. The solid blue line shows the actual assignment data, the dotted line is the simulated counterfactual using the Old Mechanism for 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.

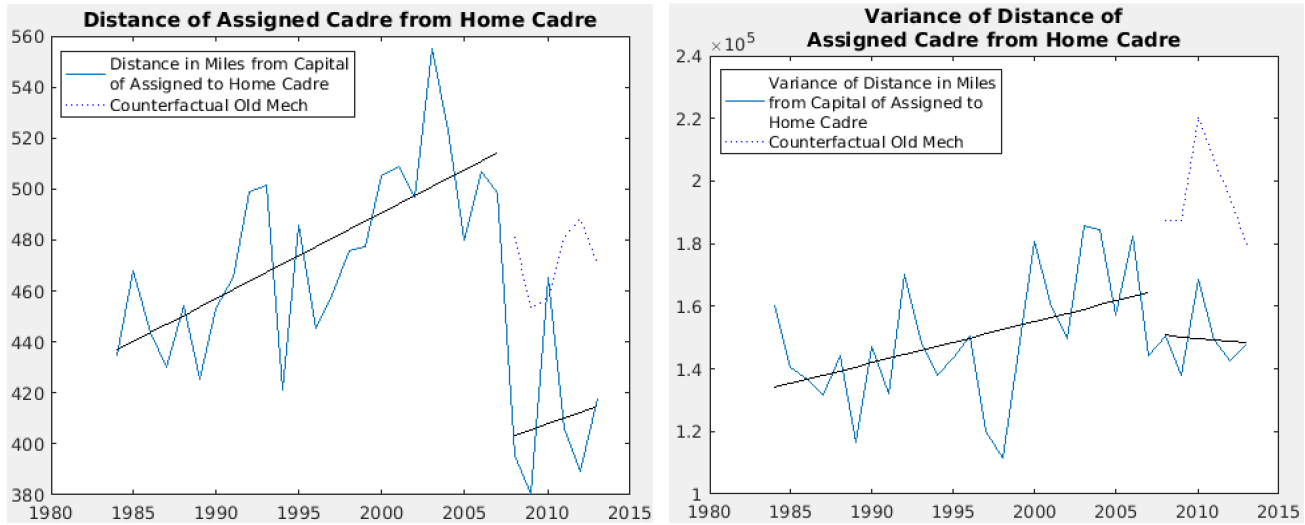


Figure 21. Comparison of what average preference rank each exam quartile gets with the New and Old Mechanism. *Top Left:* block preferences, *Top Right:* preference by closeness in distance, *Bottom Left:* uncorrelated preferences, and *Bottom Right:* reserve 3 preferences. Notice that with minimal correlation (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.

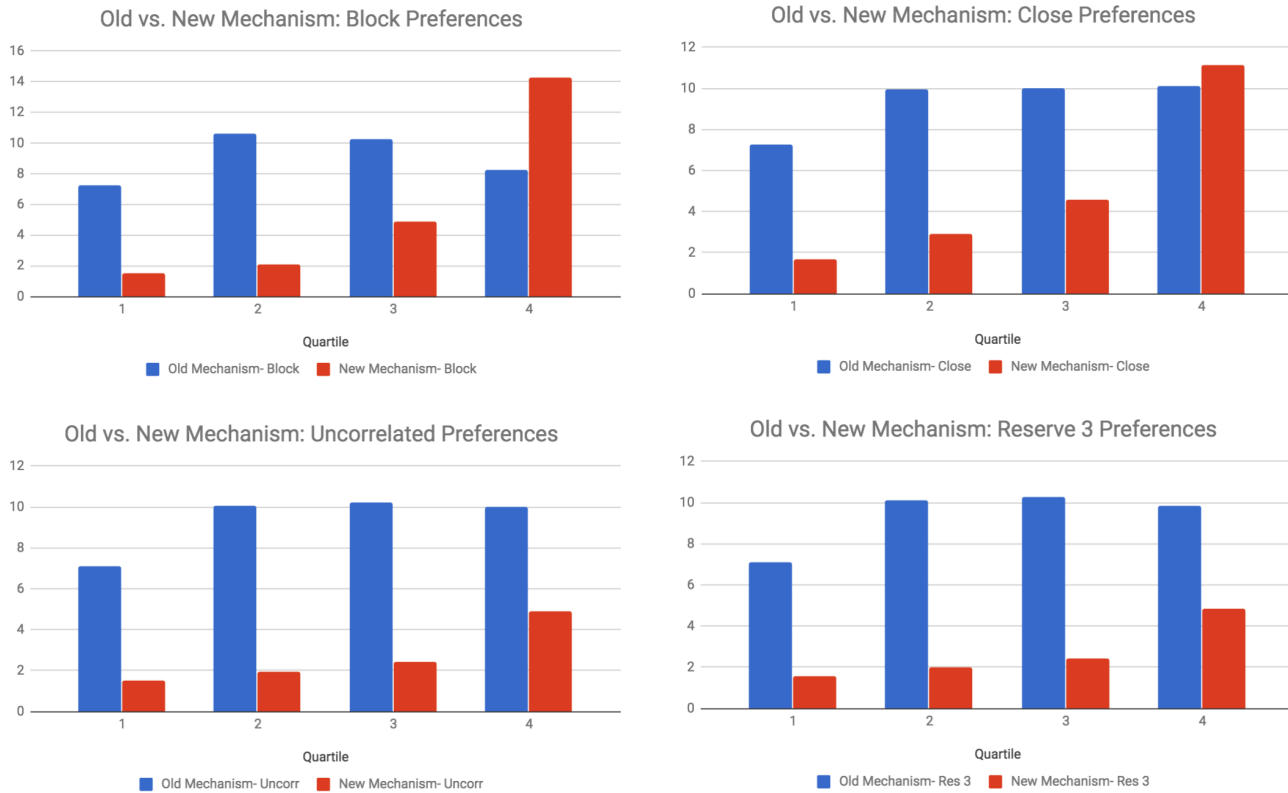


Figure 22. Own tax revenues (*Top Left*) and Non-tax revenues (*Top Right*), and Total revenues= own tax + non-tax (*Bottom*) amongst bad and good cadres for fiscal years 2005-06 to 2014-15. Fiscal year 2010-11 onwards fall under New Mechanism. We see a divergence between good and bad cadres from 2011 onwards fall under New Mechanism. Note that the jump in the Own Non-Tax Revenue occurs due to Haryana and Maharashtra; see Figure 23 for robustness.

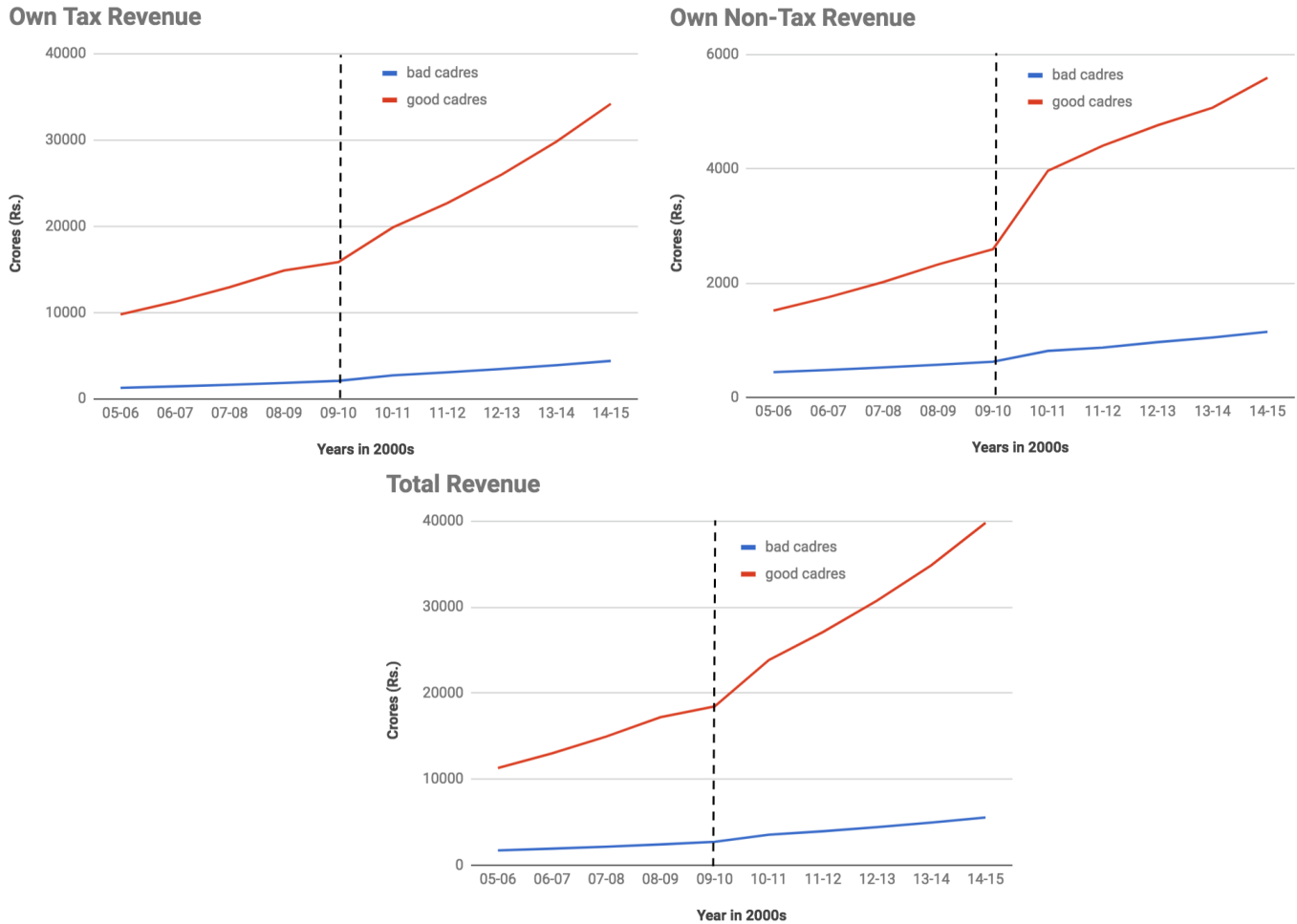


Figure 23. Robustness: The non-tax revenue graph from Figure 22 appears misleading in that good cadres appear to have done better with a jump in year 2010-11 and onwards, but this is attributed to jumps in non-tax revenue only in Haryana and Maharashtra. We show the graphs with all data (*Top Left*), excluding Maharashtra and Haryana (*Top Right*), excluding only Maharashtra (*Bottom Left*), and excluding only Haryana (*Bottom Right*). In Table 12, 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.

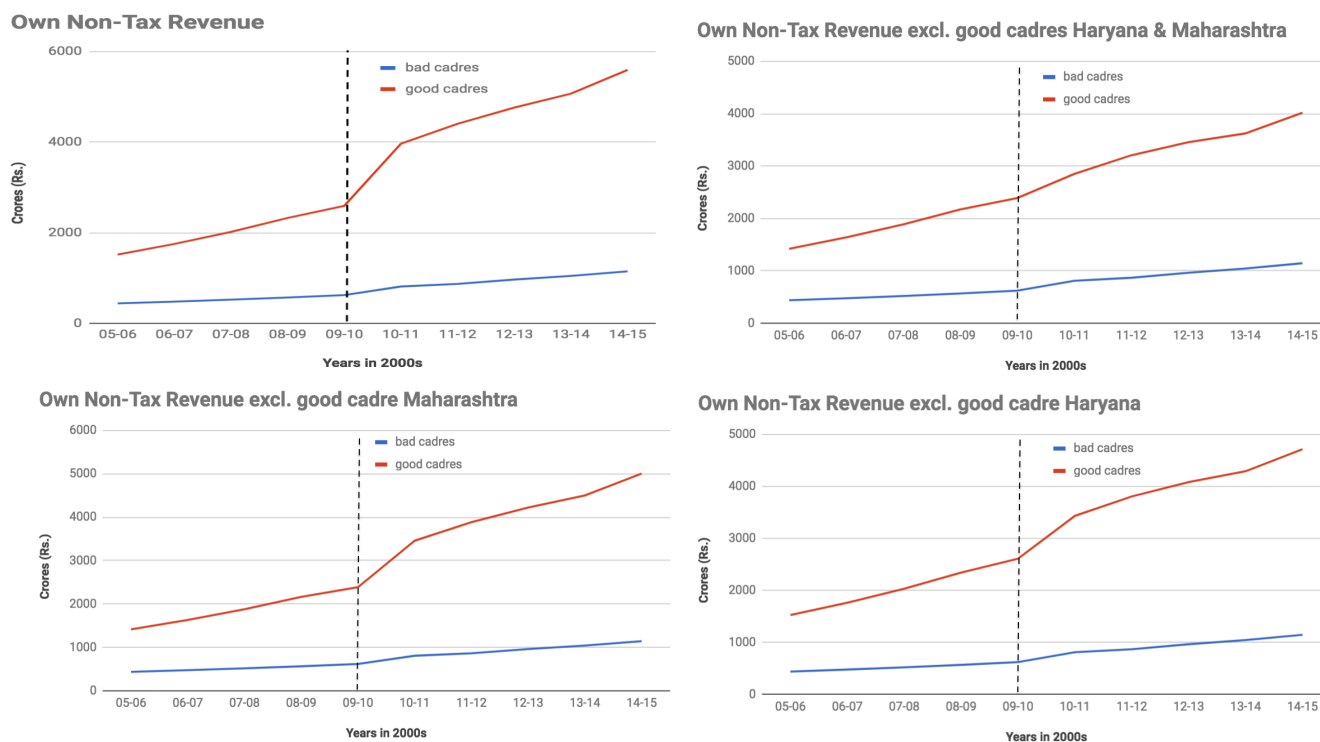


Figure 24. Detrended Own Tax Revenue (*Left*) and Detrended Non-tax Revenue (*Right*) for years 2005-06 to 2014-15 (IAS batches 2005-2012). Fiscal year 2010-11 onwards fall under New Mechanism. We see a divergence between good and bad cadres from 2011 onwards fall under New Mechanism. Note that the jump in Own Non-Tax Revenue occurs due to Haryana and Maharashtra; see Figure 25 for robustness.

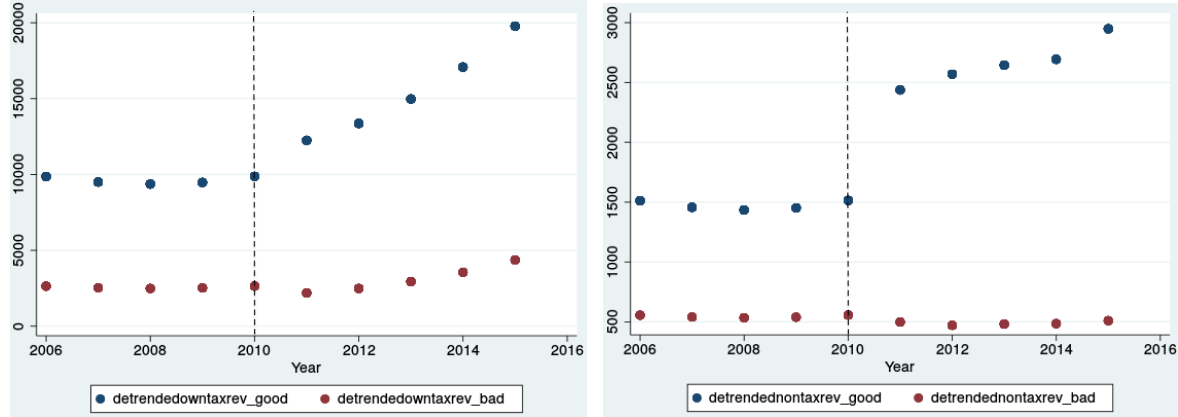


Figure 25. Robustness: The detrended non-tax revenue graph from Figure 24 appears misleading in that good cadres appear to have done better with a jump in year 2010-11 and onwards, but this is attributed to jumps in non-tax revenue only in Haryana and Maharashtra. We show the detrended graphs with all data (*Top Left*), excluding Maharashtra and Haryana (*Top Right*), excluding only Maharashtra (*Bottom Left*), and excluding only Haryana (*Bottom Right*). In Table 12, 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.

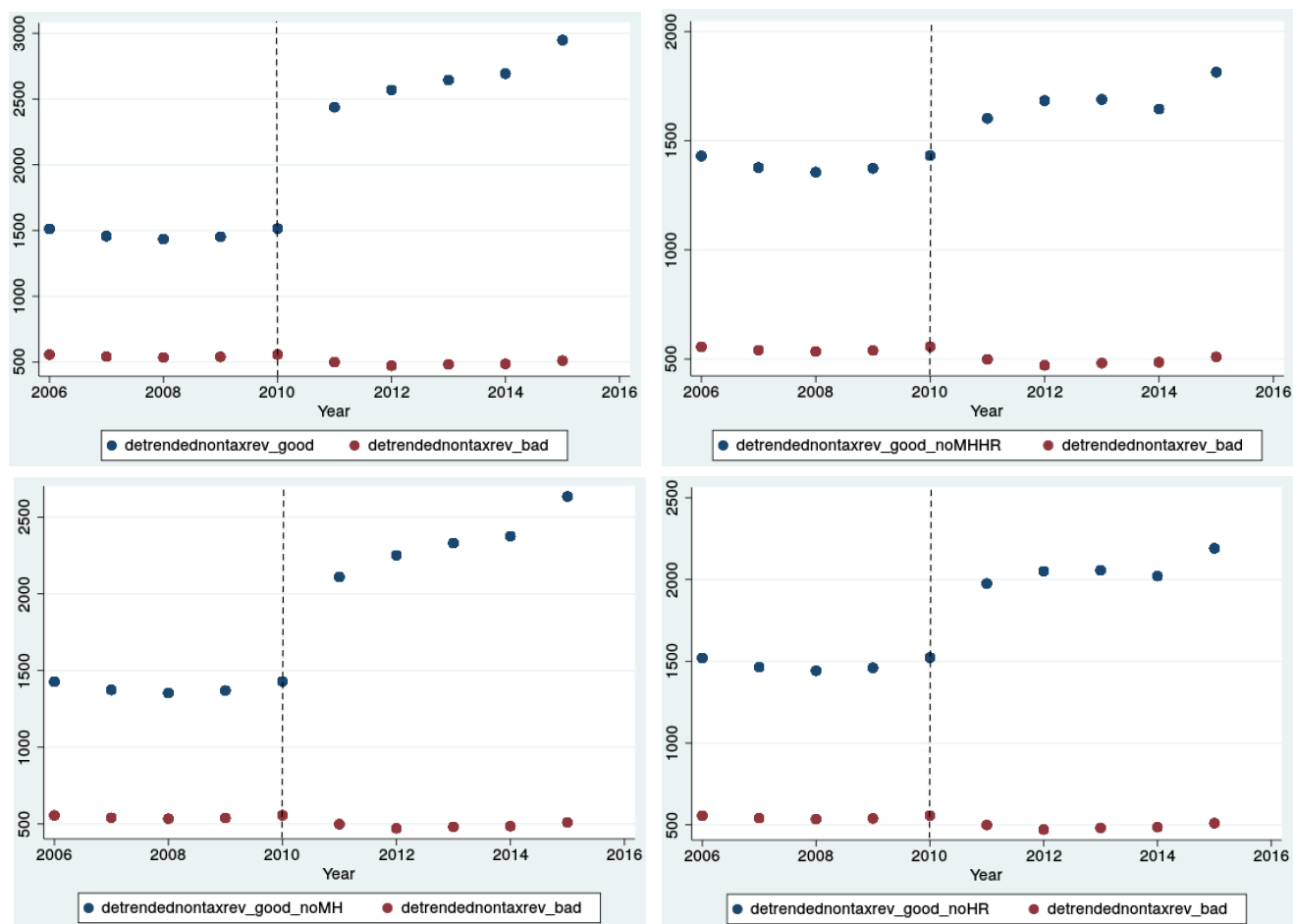


Figure 26. Plotting Human Development Index grouped by good and bad cadres from 1983 to 2012. Data used is HDI for years 1983, 1988, 1993, 2000, 2005, 2010, and 2012 constructed by Mukherjee et. al (2014). We observe a divergence in HDI across the good and bad cadres from 2010 onwards (data for years 2010 and 2012) when the IAS officers from the post-2008 New Mechanism start working.

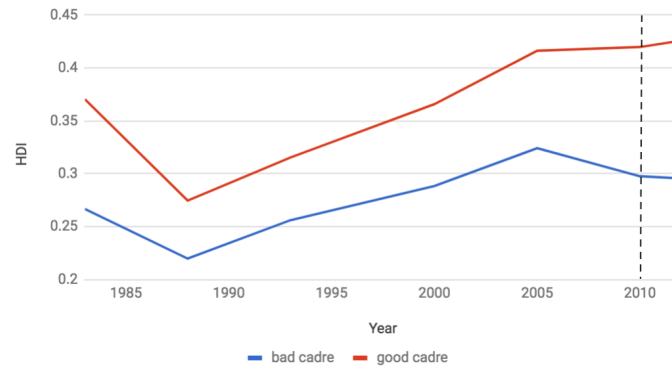


Figure 27. The percentage of top 20 exam toppers being assigned to bad cadres. The blue line is the actual assignment data and red line is the simulated counterfactual using the Old Mechanism for years 2008 onwards. Since 7 out of 24 cadres are bad, a uniform distribution of toppers would be around 30%. We see a big drop starting with the New Mechanism in 2008.

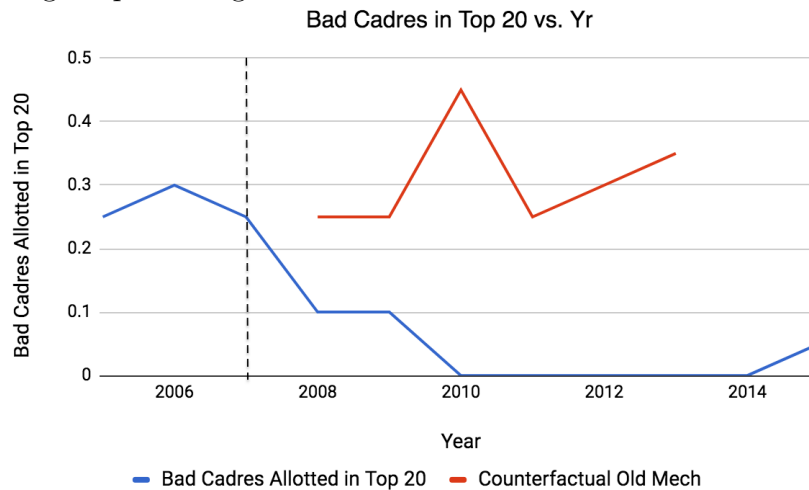


Figure 28. Difference between insiders requested and insiders assigned as a percentage of total requests. We see that there is a vast asymmetry across states and bad cadres have a harder time filling insider vacancies.

Requests - Assignments			
(Insider/Total Requests)			
2005-2007		2008-2013	
State	Ratio	State	Ratio
A G M U T	0.00	Andhra Pradesh	-0.01
Andhra Pradesh	0.00	Uttar Pradesh	0.00
Bihar	0.00	Bihar	0.00
Haryana	0.00	Haryana	0.00
Jammu & Kashmir	0.00	Jammu & Kashmir	0.00
Jharkhand	0.00	Kerala	0.00
Karnataka	0.00	Maharashtra	0.00
Kerala	0.00	Punjab	0.00
Maharashtra	0.00	Rajasthan	0.00
Orissa	0.00	Tamil Nadu	0.00
Punjab	0.00	Karnataka	0.04
Rajasthan	0.00	Himachal Pradesh	0.05
Tamil Nadu	0.00	A G M U T	0.05
Uttar Pradesh	0.00	Jharkhand	0.08
Uttarakhand	0.00	Orissa	0.08
Madhya Pradesh	0.06	Madhya Pradesh	0.10
West Bengal	0.07	Gujarat	0.15
Manipur Tripura	0.13	Manipur Tripura	0.16
Gujarat	0.18	Assam Meghalaya	0.18
Himachal Pradesh	0.25	Chhattisgarh	0.19
Nagaland	0.25	Uttarakhand	0.22
Sikkim	0.25	West Bengal	0.23
Assam Meghalaya	0.27	Nagaland	0.32
Chhattisgarh	0.28	Sikkim	0.43

Figure 29. t-statistic comparisons of various simulated mechanisms with actual assignments. We notice that the ranking of one-sided cadre allocation mechanisms from Section 6.1 approximately holds in the data.

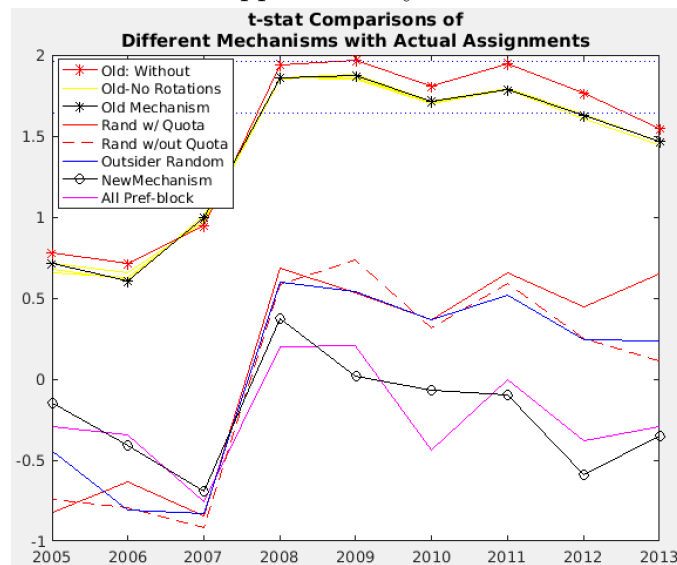


Figure 30. *Top Left:* percent of across-cadre mean of average exam rank by cadre which are lower in the simulated mechanism than in the actual assignments. *Top Right:* percent of across-cadre variance of average exam rank by cadre which are lower in the simulated mechanism than in the actual assignments. *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 6.1 approximately holds in the data.

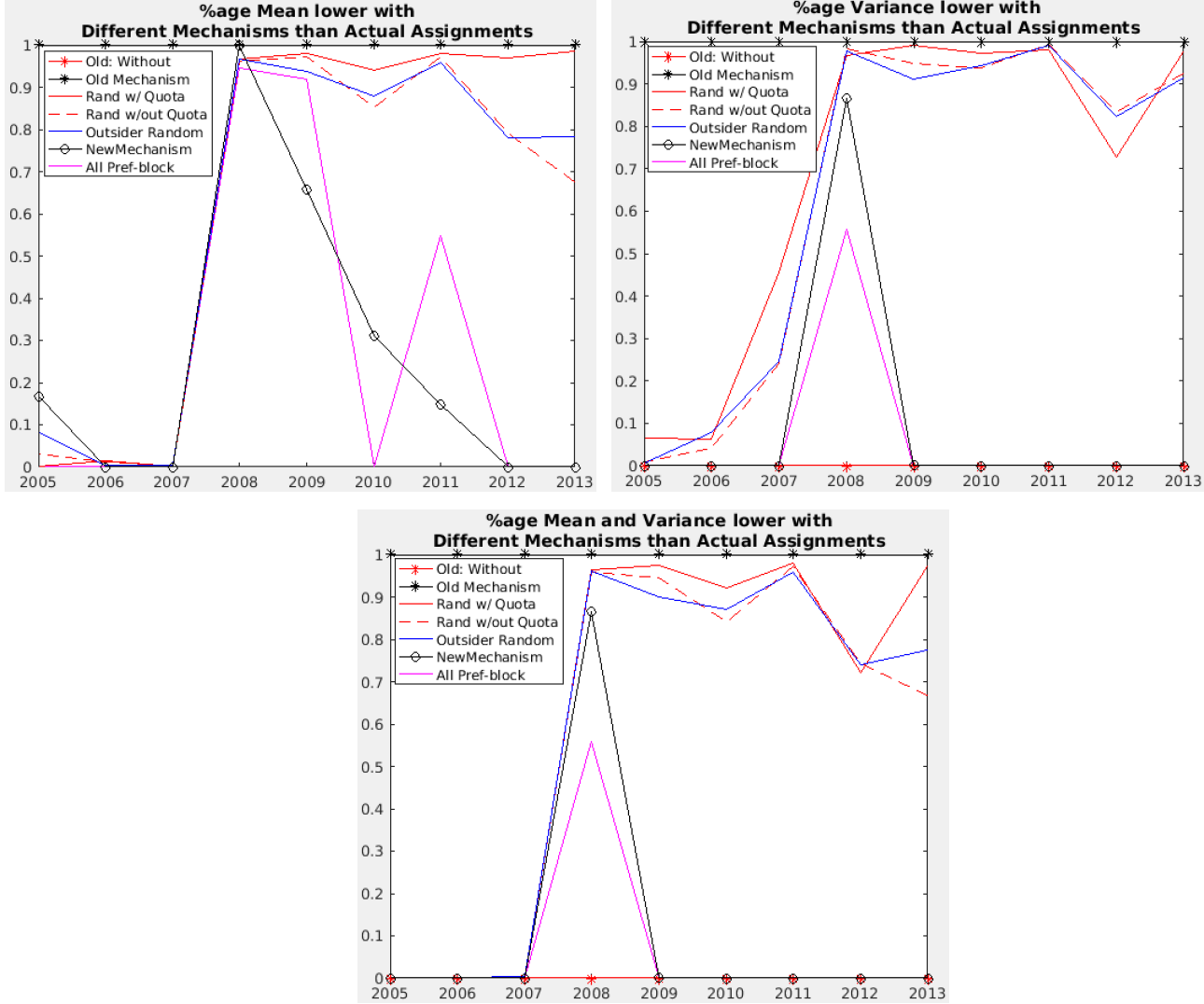


Figure 31. t-statistic comparisons of various simulated mechanisms with actual assignments. Simulations are serial dictatorship in order of exam rank given block (purple), reserve 3 (green), uncorrelated (turquoise), and close preferences (turquoise with dots). Includes simulated Old and New Mechanisms for comparison.

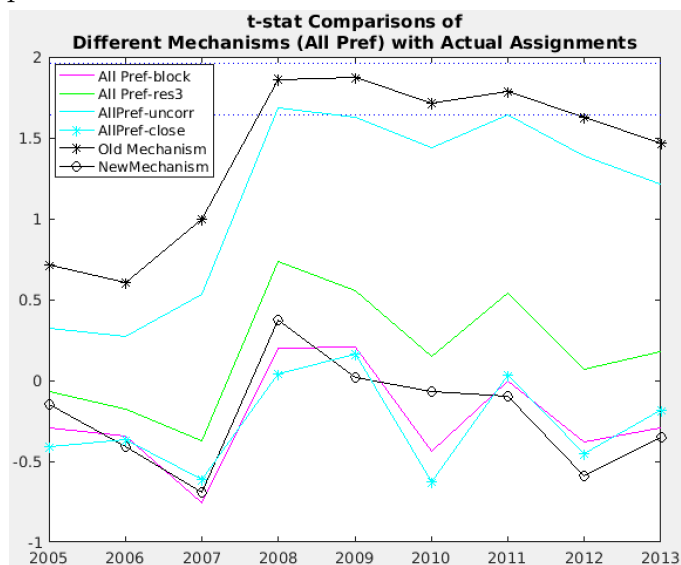


Figure 32. Proportion of toppers coming from each state/territory in Joint Cadres (Manipur-Tripura and Assam-Meghalaya) and Grouped Cadre (AG-MUT).

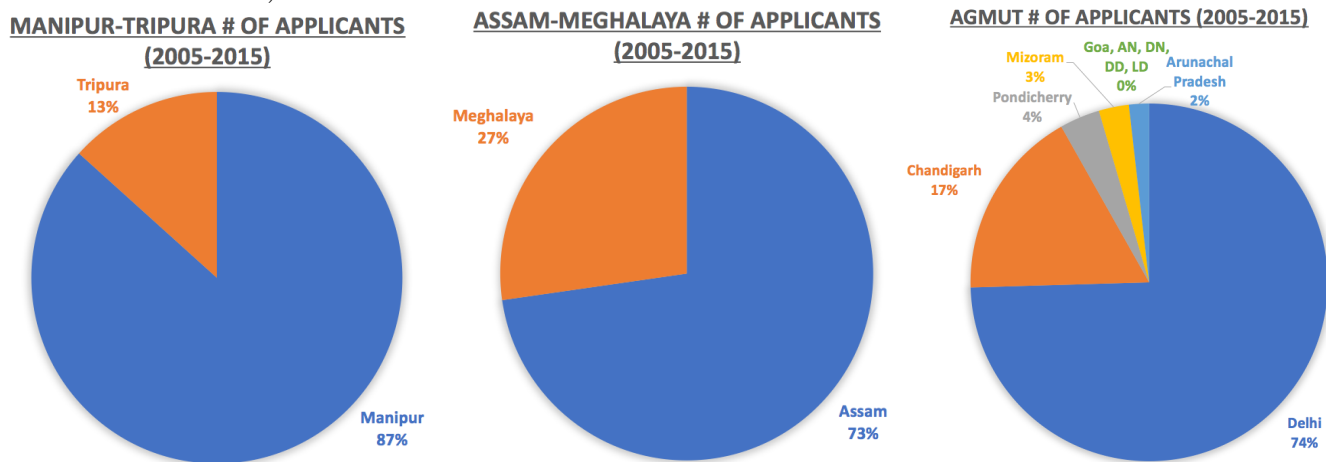


Figure 33. Number and average exam ranks of toppers coming from each cadre in the new states formed in 2000 relative to their mother states: Uttarakhnad, Jharkhand, and Chhattisgarh.

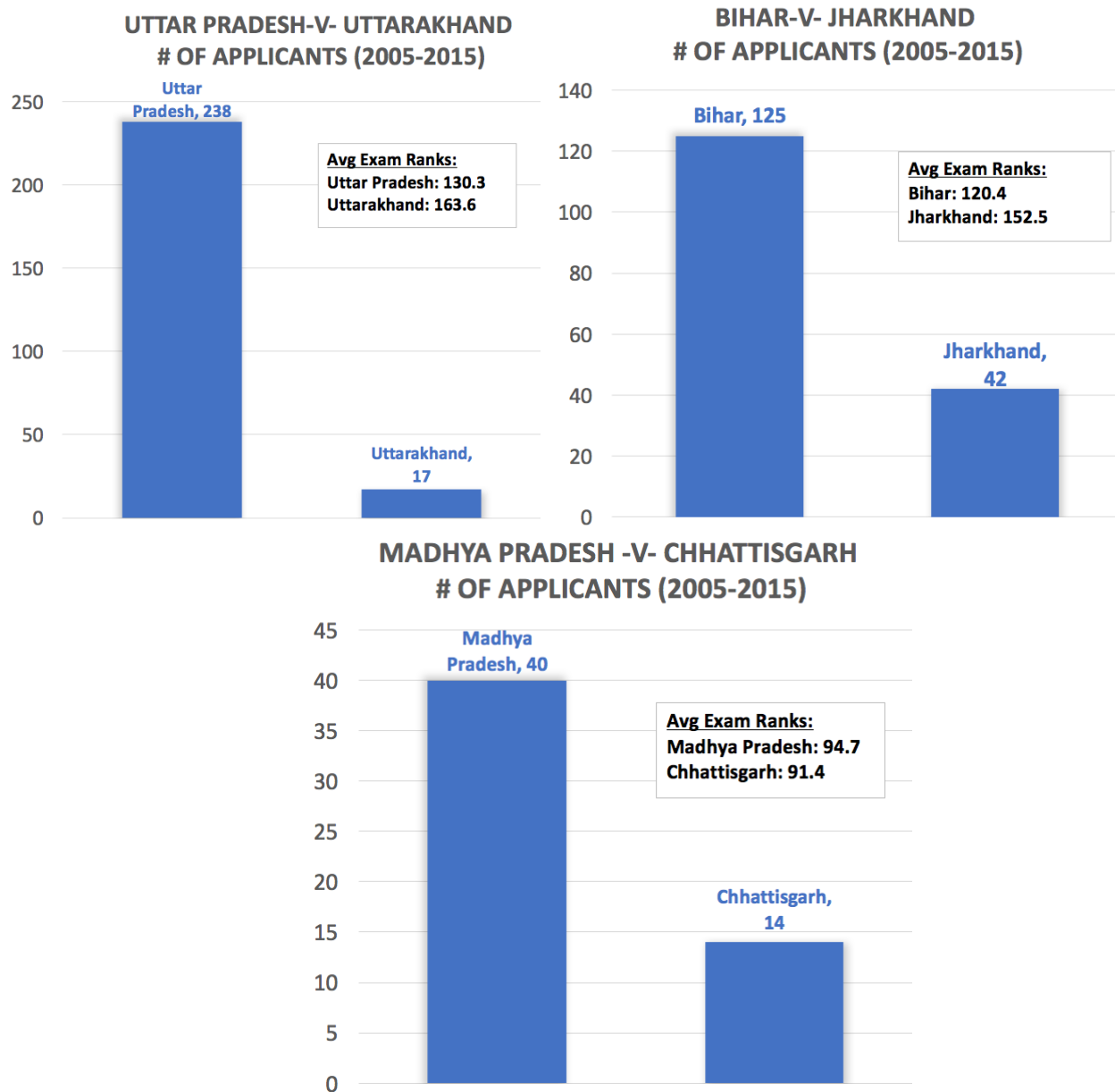


Figure 34. Number and average exam rank of toppers from Joint Cadres (Manipur-Tripura and Assam-Meghalaya) and Grouped Cadre (AGMUT).

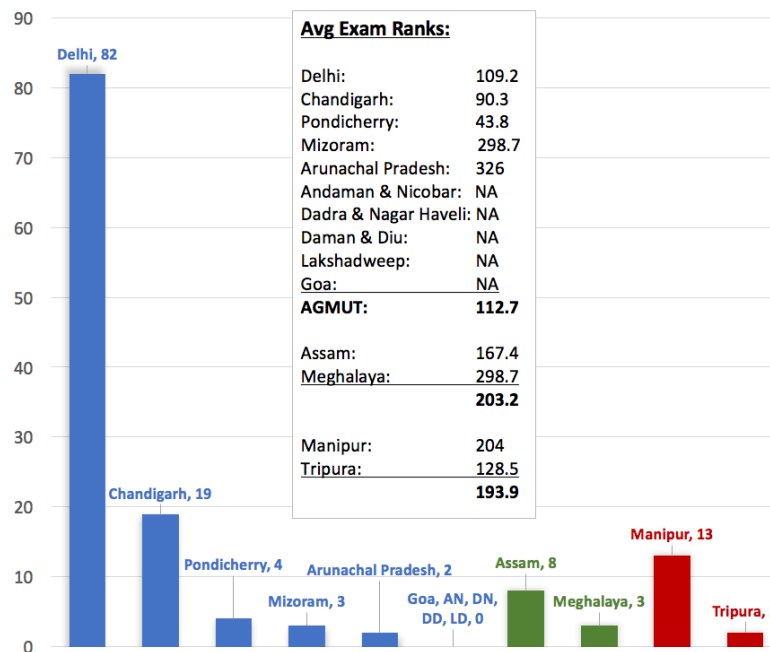


Figure 35. t-statistic comparing candidate-proposing (*Left*) and cadre-proposing (*Right*) Deferred Acceptance using various simulated preferences to Actual Assignments. Simulations for block (red), reserve 3 (blue), uncorrelated (green), and close preferences (purple). Includes simulated Old and New Mechanisms for comparison.

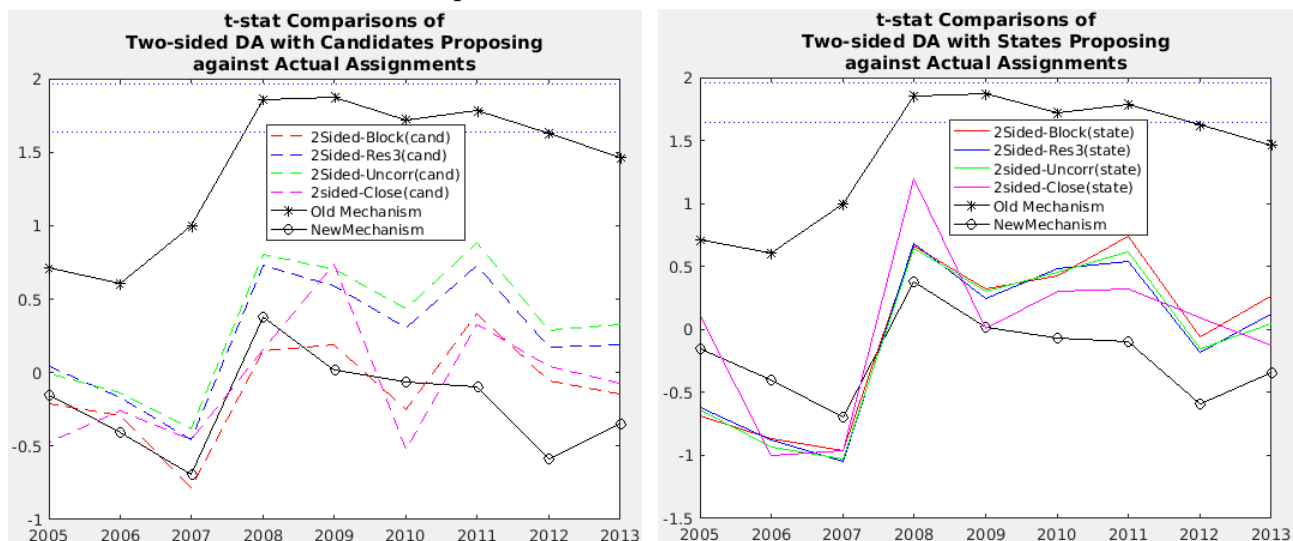


Figure 36. Percentile of average preference rank of assignment for candidates (*Left*) and states (*Right*) with Deferred Acceptance. Simulations for block (black), reserve 3 (green), uncorrelated (blue), and close preferences (red).

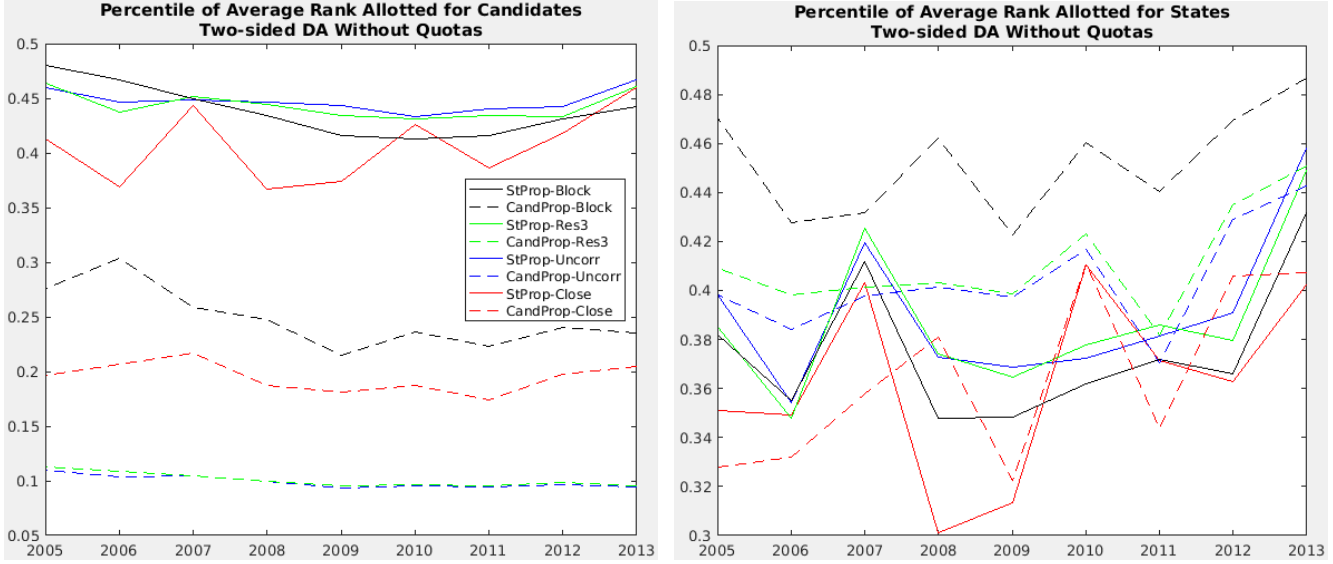


Figure 37. t-statistic comparing candidate-proposing (*Left*) and cadre-proposing (*Right*) Deferred Acceptance with insider soft constraints and various simulated preferences to Actual Assignments. Simulations for block (red), reserve 3 (blue), uncorrelated (green), and close preferences (purple). Includes simulated Old and New Mechanisms for comparison.

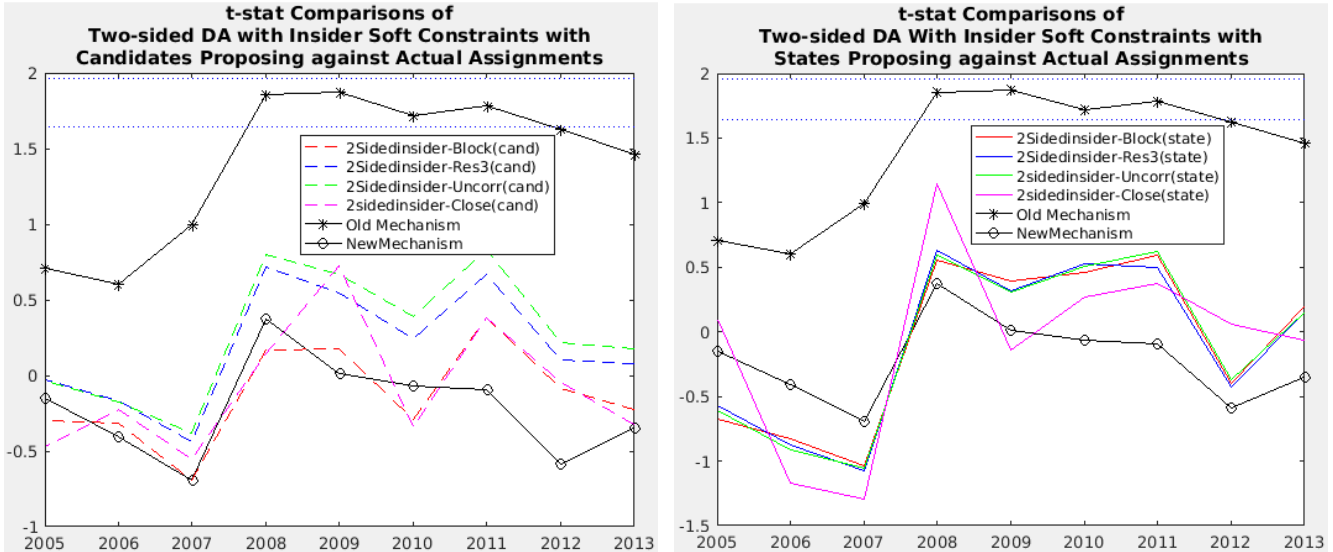


Figure 38. Percentile of average preference rank of assignment for candidates (*Left*) and states (*Right*) with Deferred Acceptance with insider soft constraints. Simulations for block (black), reserve 3 (green), uncorrelated (blue), and close preferences (red).

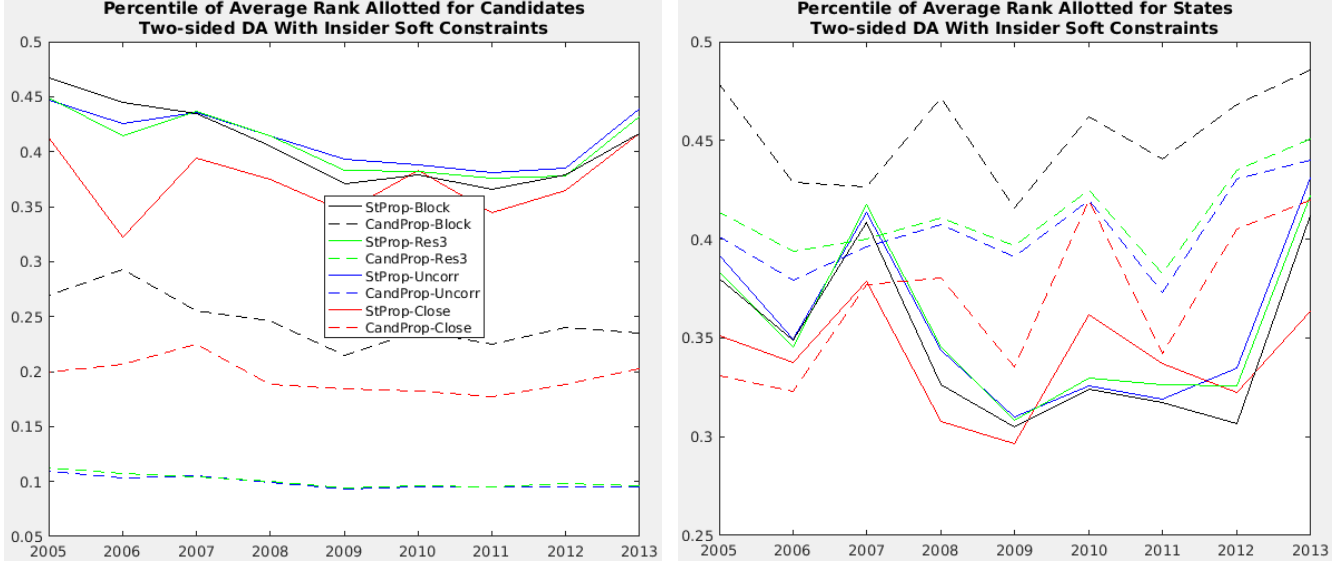


Figure 39. t-statistic comparing candidate-proposing (*Left*) and cadre-proposing (*Right*) Deferred Acceptance with quota soft constraints and various simulated preferences to Actual Assignments. Simulations for block (red), reserve 3 (blue), uncorrelated (green), and close preferences (purple). Includes simulated Old and New Mechanisms for comparison.

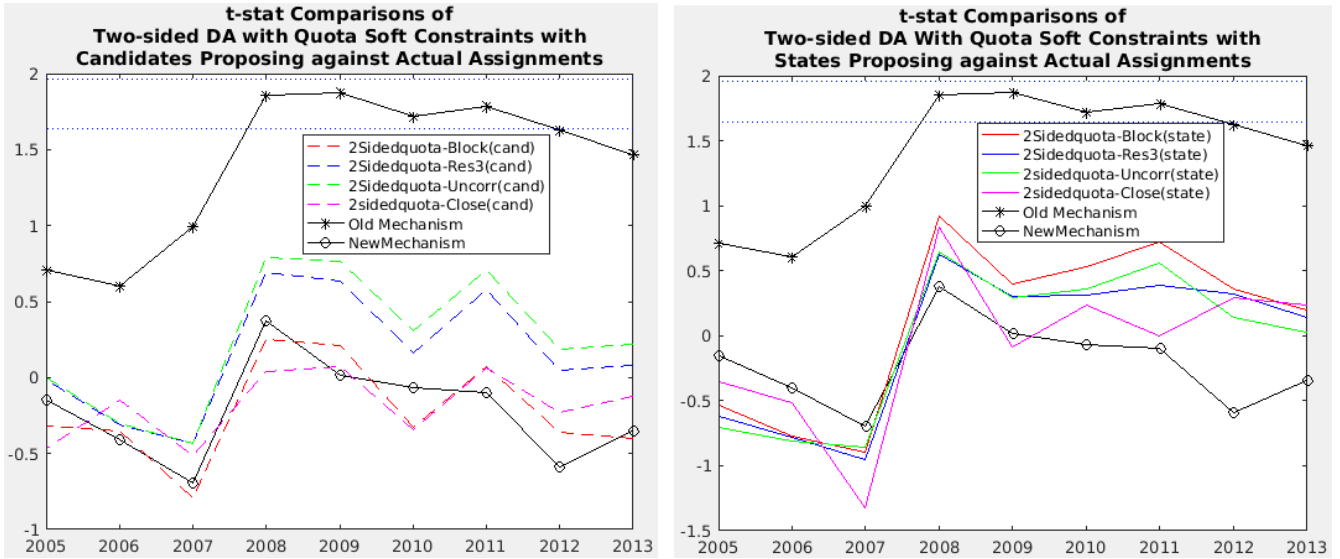


Figure 40. Percentile of average preference rank of assignment for candidates (*Left*) and states (*Right*) with Deferred Acceptance with quota soft constraints. Candidate performance is split by SC/ST category (*Top*), OBC category (*Middle*), and General category (*Bottom*). Solid (dashed) lines have states (candidates) proposing. Simulations for block (black), reserve 3 (green), uncorrelated (blue), and close preferences (red).

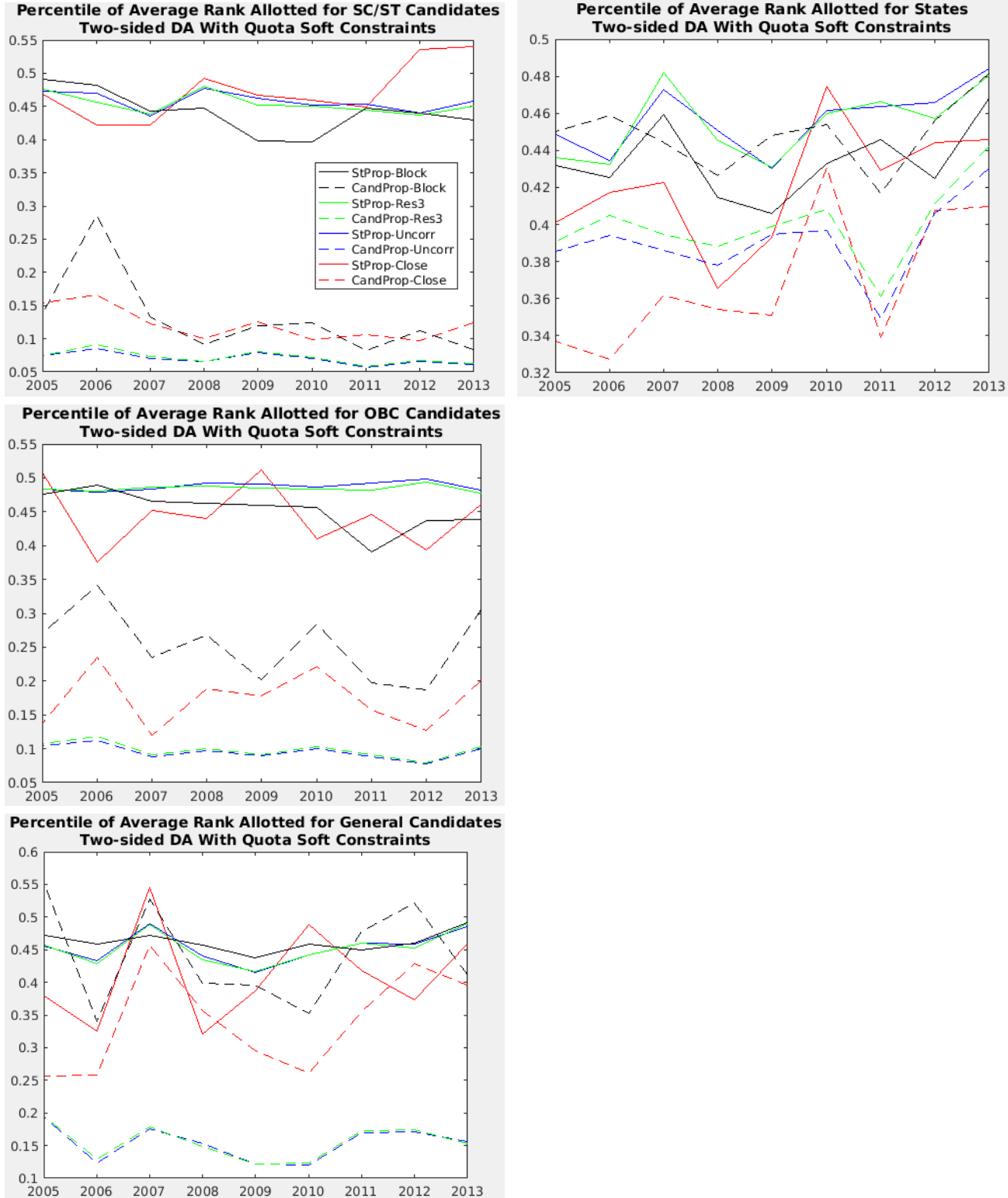


Figure 41. t-statistic comparing candidate-proposing (*Left*) and cadre-proposing (*Right*) Deferred Acceptance with quota x insider soft constraints and various simulated preferences to Actual Assignments. Simulations for block (red), reserve 3 (blue), uncorrelated (green), and close preferences (purple). Includes simulated Old and New Mechanisms for comparison.

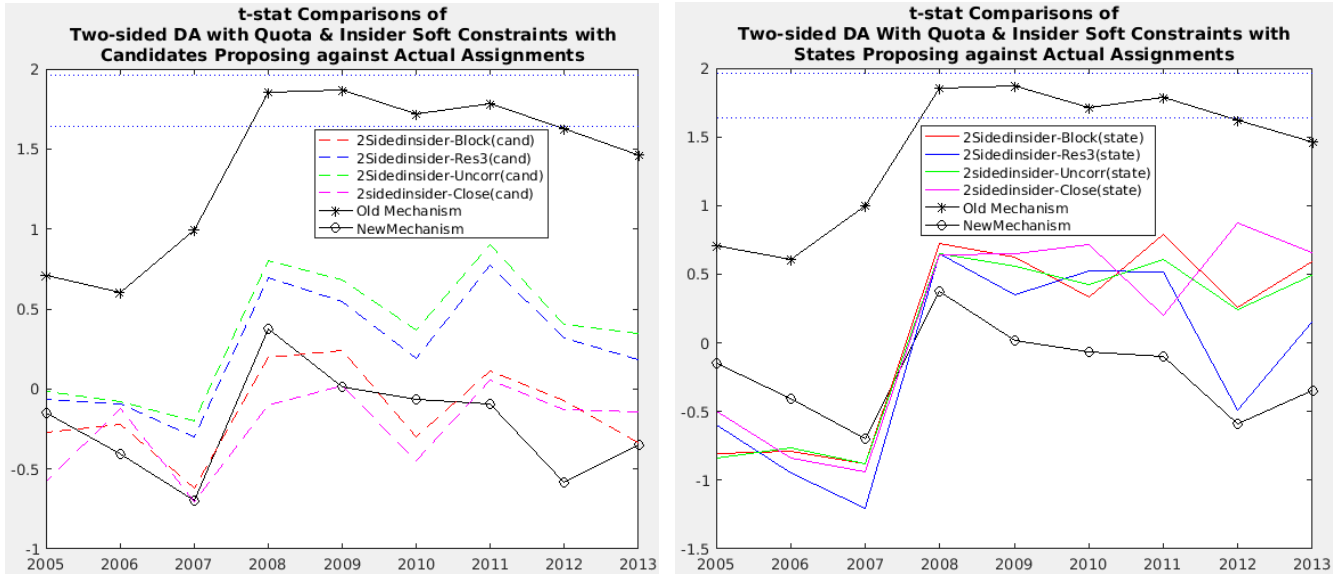


Figure 42. Percentile of average preference rank of assignment for candidates (*Left*) and states (*Right*) with Deferred Acceptance with quota x insider soft constraints. Candidate performance is split by SC/ST category (*Top*), OBC category (*Middle*), and General category (*Bottom*). Solid (dashed) lines have states (candidates) proposing. Simulations for block (black), reserve 3 (green), uncorrelated (blue), and close preferences (red).

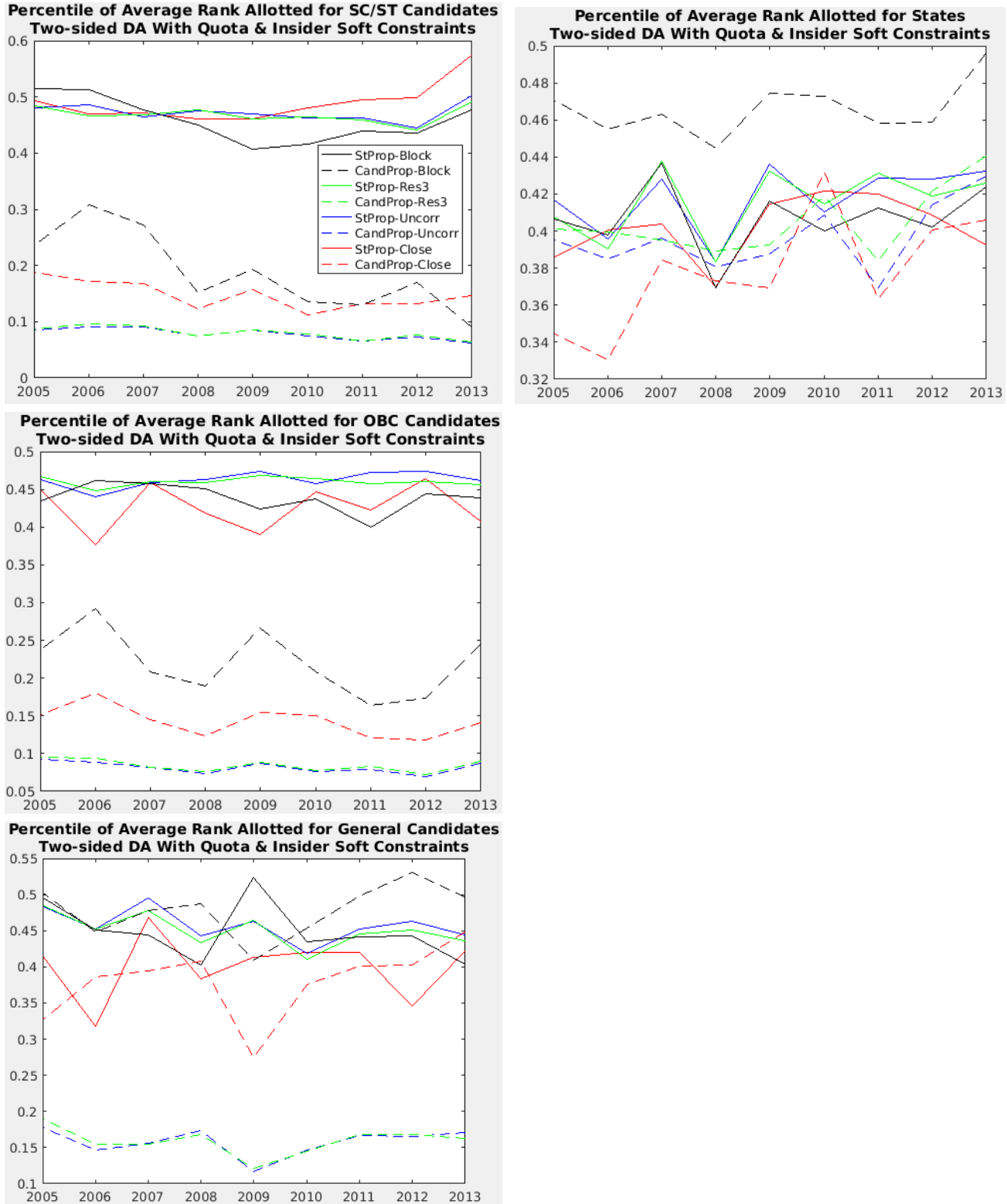
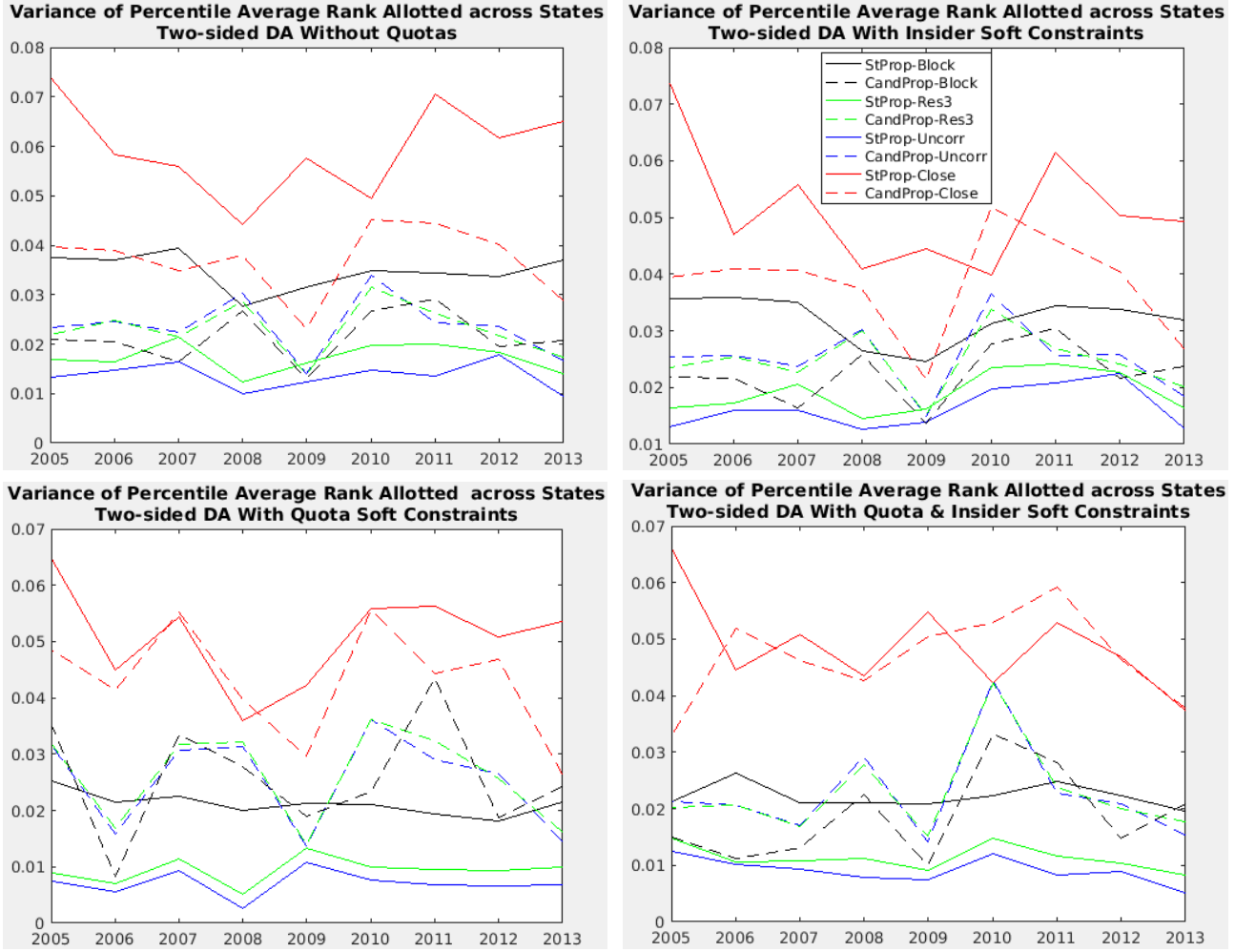


Figure 43. Variance of percentile average preference rank of assigned candidates across cadres for Deferred Acceptance with no reservations (*Top Left*), Deferred Acceptance with insider soft constraints (*Top Right*), Deferred Acceptance with quota soft constraints (*Bottom Left*), and Deferred Acceptance 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).



APPENDIX A. 2018 CADRE ALLOCATION POLICY & STRATEGYPROOFNESS

The UPSC announced on 5th September, 2017 a revised cadre allocation policy starting for the 2018 batches onwards, which is the New Mechanism discussed at length in this paper, but with an added preference order restriction for the civil servants when ranking the cadres⁶³. We discussed such a possibility in Section 6.3 prior to the announcement of this new policy. In this appendix, we describe the preference order restriction and show why such a restriction renders the system non-strategyproof.

The 2018 revised cadre allocation policy 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 first 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
- (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) ...

Two other important caveats are important:

- (1) To qualify for insider vacancy, candidate must rank Zone containing his home cadre as his 1st choice, and must rank his home cadre as the 1st choice within that Zone⁶⁴.
- (2) Not ranking cadres or zones is treated as indifference amongst unranked cadres or zones.⁶⁵

In Section 6, we discussed the strategyproofness of various mechanisms: the Old Mechanism is theoretically not strategyproof but very ‘hard’ to game and the New Mechanism is not strategyproof because of the Insider priority. It is important to note that in the subset of non-home state cadres, ranking is strategyproof under the New Mechanism, as it is based on

⁶³See <https://easy.nic.incsePlusDocscadrepolicy2017.pdf> for official 2018 policy.

⁶⁴“A candidate shall be allotted to his Home cadre, on the basis of his merit, preference and vacancy available at his turn in his category. For allocation to Home cadre against an Insider vacancy, a candidate will be required to express his first preference to the Zone in which his Home cadre falls as well as first preference to the Home cadre within that relevant Zone, otherwise he shall not be considered for his Home cadre at all.” (2018 Cadre Allocation Policy)

⁶⁵“If a candidate does not give any preference for any of the Zones/Cadres, it will be presumed that he has no specific preference for those Zones/cadres. Accordingly, if he is not allocated to any one of the cadres for which he has indicated the preference, he shall be allotted along with other such candidates in the order of rank to any of the remaining cadres, arranged in an 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.” (2018 Cadre Allocation Policy)

a serial dictatorship by exam rank. The 2018 mechanism is the same as the New Mechanism with the added preference restrictions described above. These preference restrictions render the mechanism non-strategyproof, even amongst the subset of non-home state cadres.

With a simple model with a numerical example below, we emphasize two points:

- (1) The 2018 Cadre Allocation Policy is not strategyproof for cadre preference within a zone (we call “intra-zonal strategyproofness”)
- (2) The 2018 Cadre Allocation Policy is not strategyproof for zonal preferences across zones (we call “inter-zonal strategyproofness”)

Consider the 2018 Cadre Allocation Policy 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 $b \succ a$ in Z_1 and $c \succ d$ in Z_2 (violating intra-zonal strategyproofness) with the following example:

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

Notice, that for the home cadre c , 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 will not get his home cadre.

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 probability (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. Hence, $Z_2 \succ Z_1$, violating inter-zonal strategyproofness. Moreover, although $v_a > v_b, p_b > p_a$, and hence, to avoid failure and get the worst cadre $v_b \gg v_d$ with a high probability of .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 high probability and avoid getting d , instead of getting a with small probability and then get the bad outcome d . This violates intra-zonal strategyproofness as the stated preference is $b \succ a$ in Z_1 .

This model abstracts away equilibrium environment being played across many candidates, differences in information across candidates, etc. Instead, we simplify 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.

APPENDIX B. 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 a mechanism to allocate the exact service within the many civil services which take the Civil Services Exam.

The entire process is as follows: i) candidates take the preliminary exam, ii) those who qualify to appear for the main exam report their service preferences⁶⁶, iii) those who are selected from the main exam are assigned to service via Service Allocation Mechanism, and finally, iv) each service then conducts its relevant training and within service allocation⁶⁷. Note that unlike in IPS and IAS, 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 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 within those who are allotted to 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 exam, how toppers (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 spots, the inequality does not necessarily hold. For example, being 10th vs 11th might get you 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.

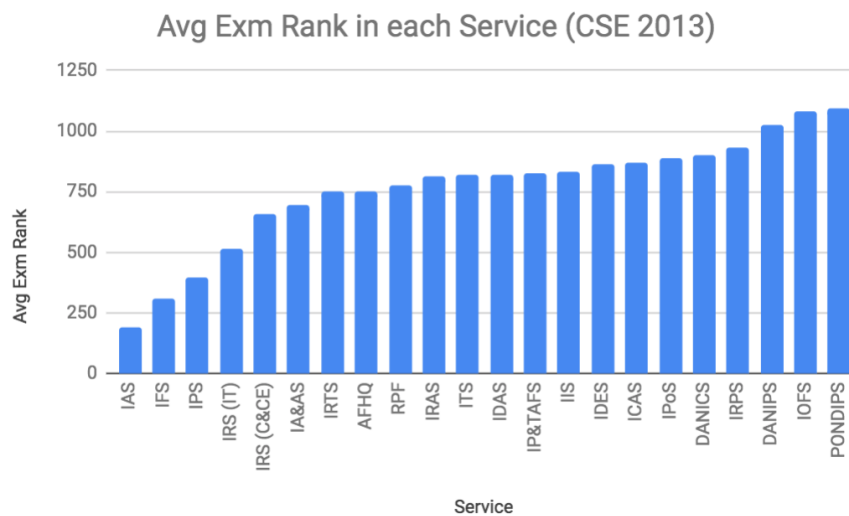
⁶⁶The services which follow under the common Civil Service Examination are i. Indian Administrative Service (IAS), ii. Indian Foreign Service, iii. Indian Police Service, iv. Indian P&T Accounts & Finance Service, Group 'A', v. Indian Audit & Accounts Service, Group 'A', vi. Indian Customs & Central 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'

⁶⁷Both 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 making the application. The total number of vacancies and service-wise breakdown is announced in the advertisement, but the number of vacancies in each cadre/state is not known.

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 toppers opt for the IAS, followed by IFS and IPS, and then followed by a mix of the other civil services. Figures 44 and 45 show that the lowest average exam rank services 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 toppers are such that they prefer every IAS cadre allocation to any IPS, IFS or other service position; however, suppose they 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 say there is a big chance he gets an insider position in the IPS, but not the IAS.

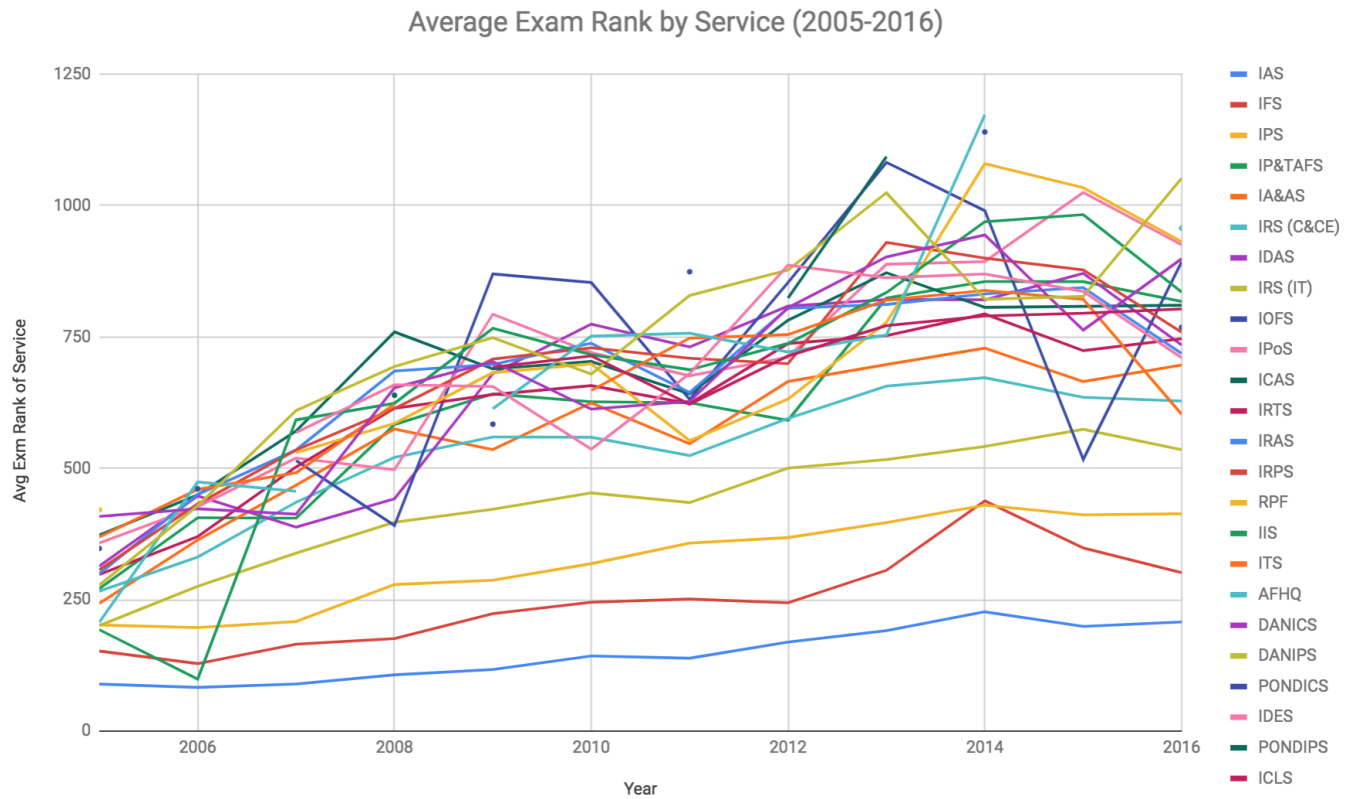
Figure 44. We plot the average exam rank in the Civil Service Examination for year 2013 across the various services. Notice that IAS, IFS, IPS, and IRS have the lowest average exam rank, consistent with being the most sought-after services.



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

Overall, the fact that the overall system involves nested matching mechanisms, even two serial dictatorship in order of exam rank, which are strategyproof in isolation, when combined in this nested manner, render the entire system non-strategyproof in the first step.

Figure 45. We plot the average exam rank in the Civil Service Examination for years 2005-2016 across various services. Notice that IAS, IFS, IPS, and IRS are always amongst the the lowest average exam rank services, consistent with being the most sought-after services.



APPENDIX C. OTHER ALL-INDIA SERVICES: INDIAN POLICE SERVICES & INDIAN 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.

Table 21. Preferences of 122 IPS officers admitted from the 2008 Civil Service Examination. 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 amongst the last in IPS officers' rank order preferences. *Data from* http://mha.nic.in/hindi/sites/upload_files/mhahindi/files/pdf/CardAllokts2008.pdf

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

Figure 46. *Top:* average exam rank of assigned IPS candidates across good and bad cadres. *Bottom:* variance of average exam rank of assigned IPS candidates across 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 the same imbalance on the quality dimension as IAS with the New Mechanism since All India Services use the same cadre assignment mechanisms. 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

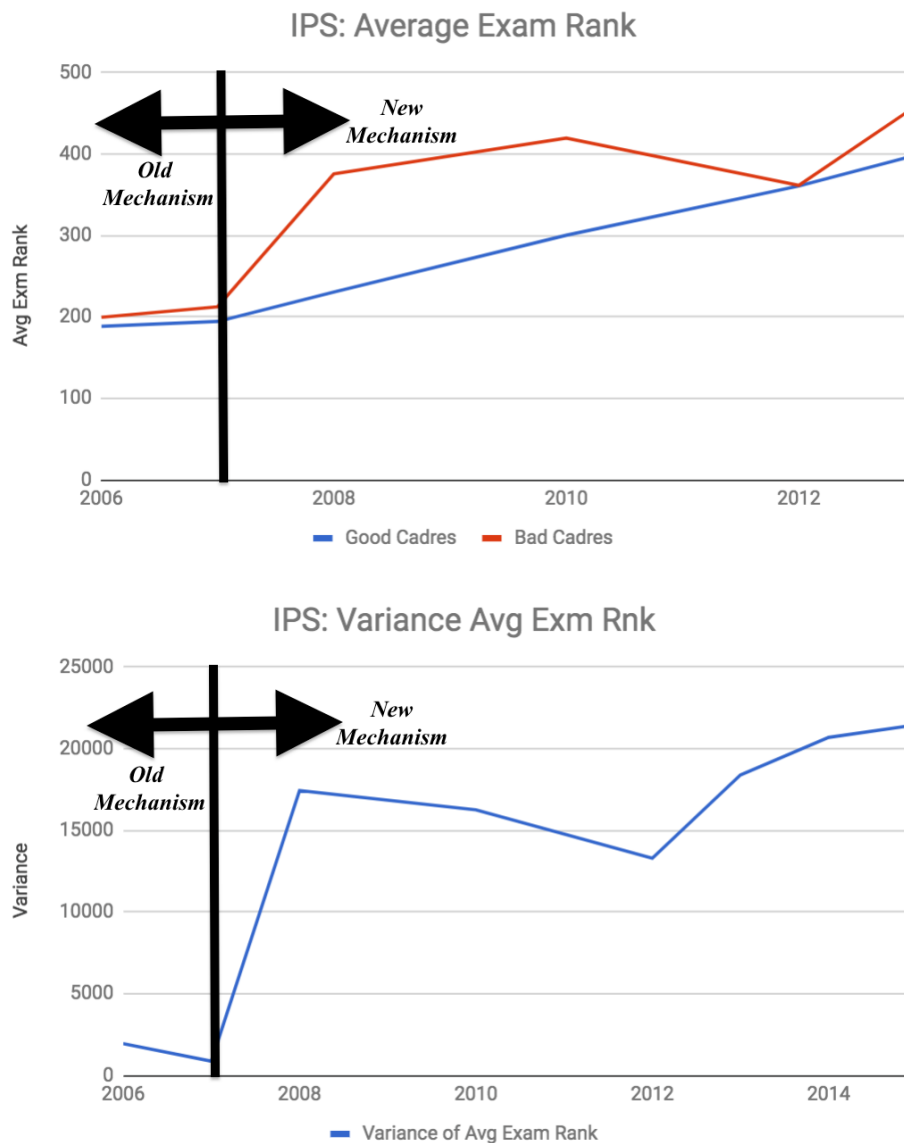


Figure 47. The figures show the occurrence rate of the cadres among the 5 *most preferred* cadres (*Top Left*) and the 5 *least preferred* cadres (*Right*). Notice that bad cadres are consistently preferred amongst the 5 least preferred cadres and seem to rarely be top preference of IPS officers.

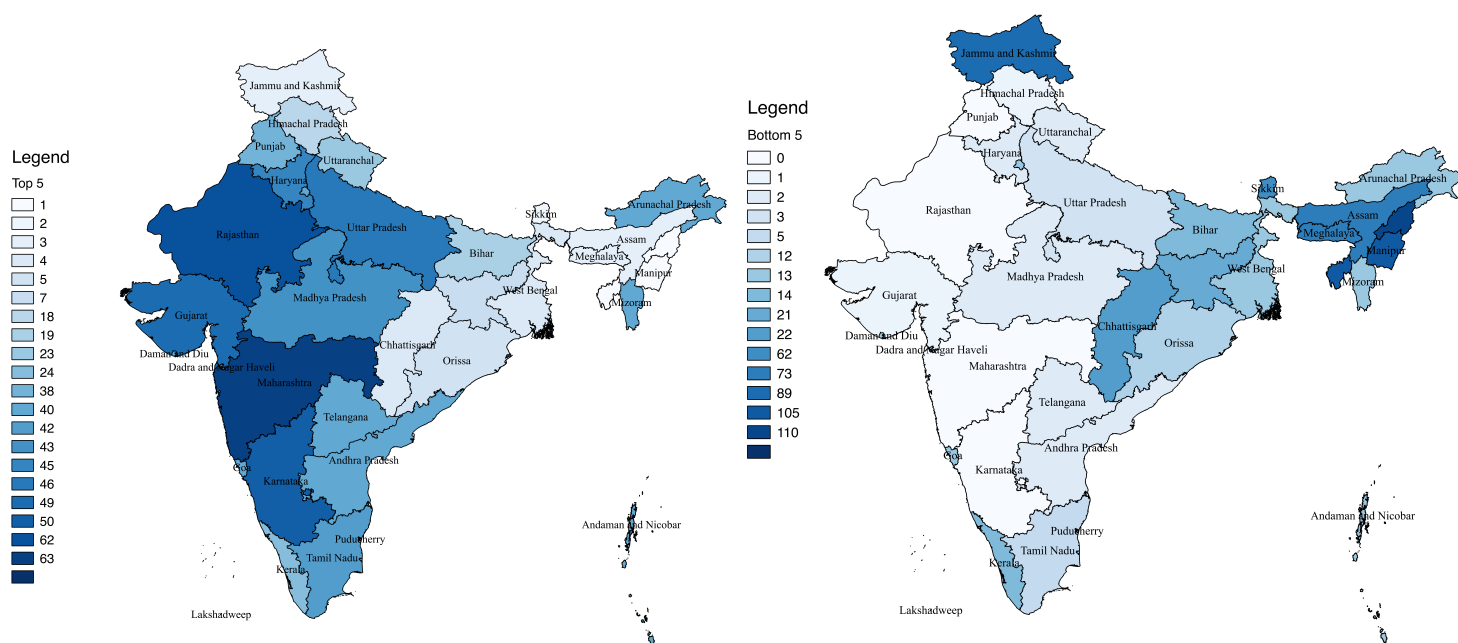


Table 22. The number of cadres ranked by 122 IPS officers admitted from the 2008 Civil Service Examination. 93% of IPS officers gave complete preferences (with some indifference). 121 out of 122 indicated wanting to be an insider (i.e., 1st choice was home cadre). Note that no cadre can be deemed unacceptable, 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

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

Table 23. Preference of 110 IFoS officers admitted from the 2015 and 2016 Civil Service Examinations . The left columns show the average rank (out of 26 cadres) IFoS officers assigned to each cadre, while the right columns show the standard deviation of rank assigned to each cadre. Notice the bad cadres (*bolded*) are consistently ranked amongst the last in IFoS officers' rank order preferences. *Data from <http://ifs.nic.in>*

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

APPENDIX D. QUALITATIVE DESCRIPTION OF OTHER MARKET DESIGN CONSIDERATIONS AND POLICIES

In this appendix, we qualitatively describe four important discussions which arose during interviews with IAS officers, 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 talks with various IAS officers.

D.1. Marriage amongst Civil Servants.

Apart from extreme scenarios, essentially the only way an All-India Services officer can get a permanent change in the 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 years⁶⁸. Rules dictating possible cadre changes as a result of two All-India Services officers getting married have changed over the years⁶⁹ and requests are dealt with on a case-by-case basis by the Department of Personnel and Training.

Currently, there are a few considerations taking 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 requesting a move to a cadre where a spouse has been originally assigned to, considerations for whether this cadre is under- or over-prescribed relative to its need and strength are considered. 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 rule considerations. Finally, some IAS officers choose to remain in two separate cadres and take on temporary deputations to each other or contemporaneously to a shared third cadre. Which of the four option the 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.

⁶⁸See <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.

⁶⁹See <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.

D.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 2016⁷⁰), 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

D.3. State Civil Service Promotion.

While we focus in this paper on the cadre allocation policies for direct recruits, 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. who enter by qualifying from the Civil Service Examination, another entry into the IAS is via promotion from the state civil service⁷¹.

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

⁷⁰See <https://economictimes.indiatimes.com/news/politics-and-nation/centre-increases-inter-cadre-deputation-period-up-to-five-years/articleshow/51882169.cms>

⁷¹See <https://timesofindia.indiatimes.com/india/Exams-for-state-civil-services-officers-for-promotion-to-IAS/articleshow/27861653.cms>

years. Finally, promotion to All-India Services requires the approval of a minister, and hence, concerns of favoritism have also been raised.

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>

D.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 E. 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 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 Notice⁷². The syllabus and precise weighting changes slightly across years⁷³, 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:

⁷²http://www.upsc.gov.in/sites/default/files/Engl_CSP_2017.pdf. This official notice provides a more detailed syllabus.

⁷³The 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 I (300) and Iii (300), Optional Iii(300) and Ilii(300), and Interview (300), and post-2012 (2025 points) system explained 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 24. Effect of Mechanism on Exam Rank by State: Year-by-year Effects & Placebo tests

This table expands upon the difference-in-difference specifications for average exam ranks (col 1-3) and normalized state exam ranks (col 4-6) from Table 1, 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.

	(1) StAvgExmRnk	(2) StAvgExmRnk	(3) StAvgExmRnk	(4) NormalizedStExmRnk	(5) NormalizedStExmRnk	(6) NormalizedStExmRnk
badcadrenewmech	114.8*** (24.56)			0.784*** (0.202)		
bad08		46.58 (59.47)	52.27 (62.89)		0.396 (0.506)	0.456 (0.546)
bad09		153.6*** (49.01)	159.2*** (53.76)		1.136*** (0.383)	1.196*** (0.439)
bad10		148.1*** (30.78)	153.8*** (33.20)		0.995*** (0.201)	1.056*** (0.246)
bad11		110.3** (56.03)	115.9* (63.90)		0.862* (0.444)	0.923* (0.530)
bad12		82.10* (46.05)	87.79** (44.66)		0.475* (0.271)	0.536* (0.278)
bad13		148.2*** (44.32)	153.9*** (46.07)		0.838*** (0.236)	0.899*** (0.276)
bad07			1.425 (26.73)			0.0163 (0.283)
bad06			15.64 (25.02)			0.166 (0.265)
Constant	72.99*** (9.514)	72.99*** (9.647)	74.65*** (11.18)	-0.153* (0.0925)	-0.153 (0.0938)	-0.135 (0.111)
Year FE	✓	✓	✓	✓	✓	✓
State FE	✓	✓	✓	✓	✓	✓
Observations	216	216	216	216	216	216

Standard errors in parentheses are clustered at the state cadre level

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