The Long-Run Costs of Highly Competitive Exams for Government Jobs

(Mangal, 2024: JDevE)

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AERG

Motivation

- Extreme competition in merit-based exams to select public sector workers
  - In India, China, Brazil, and Southern Europe, selection rates are often 1% or less
- Exam preparation
  - An investment in general human capital
  - Time, psychological and social costs of not getting selected

Research question

- The impacts of a policy that increased the competitiveness of public sector recruitment exams

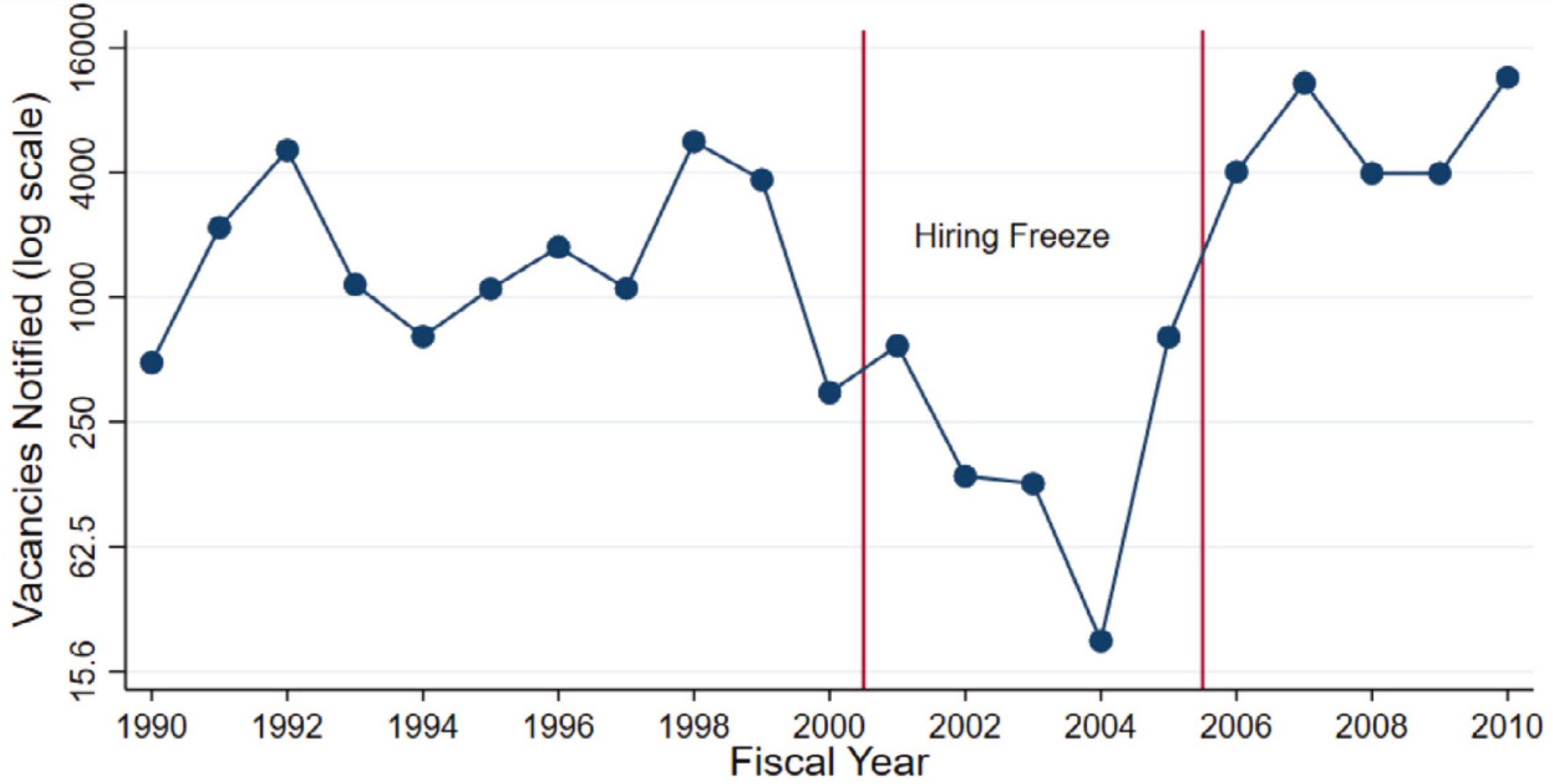
  - How individuals' employment, earnings, and household formation were affected in the long run

Institutional background: The hiring freeze

- The Government of Tamil Nadu suspended recruitment between Nov. 2001 and Jul. 2006 in India
  - Followed a state financial crisis triggered by a set of pay raises for government employees in the late 1990s
  - Exempted posts: Doctors, police constabulary, and teachers
  - Impacted posts: Unspecialized administrative posts; The average number of vacancies notified dropped by about 86%
- Group recruitments: Large number of vacancies are notified and filled through a single exam
  - 93% of the impacted posts
- Uncertainty around the length of the hiring freeze and, therefore, future hiring levels
- Negligible direct effect on aggregate labor demand

Institutional background: The hiring freeze

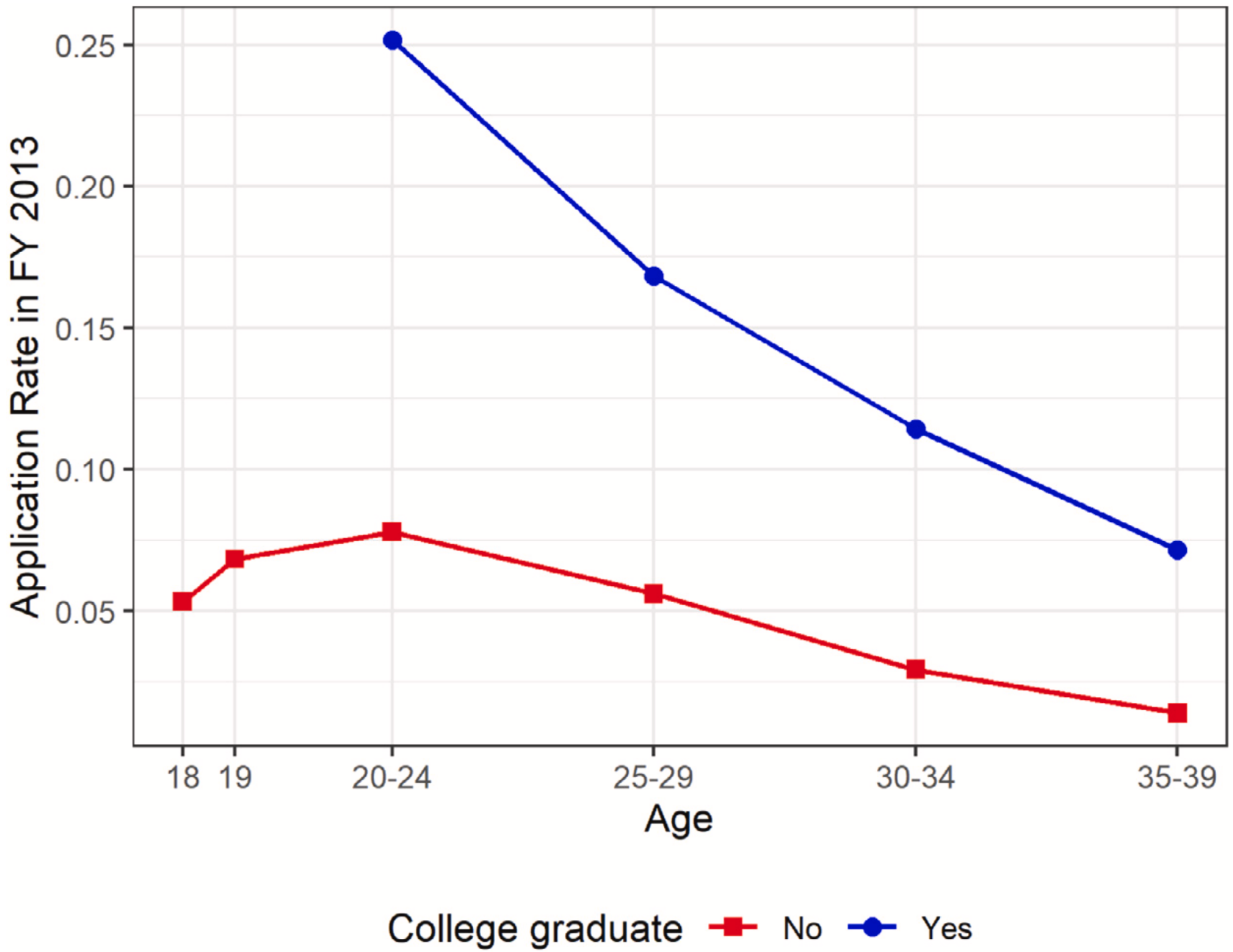
(a) Vacancies Notified



Who was impacted by the policy?

- Very few applications for government jobs in Tamil Naidu are from outside the state
- Eligibility for government jobs in India (entry level posts)
    1. 18+ years old
    2. 10^{th} standard education or higher -> higher level posts require a college degree or potentially a degree in a specific field

Who was impacted by the policy?



Deciding how much to invest in exam preparation

- Theoretically, candidates' response to the hiring freeze is ambiguous
  - Their beliefs about the probability of selection decreases
  - But the marginal returns to exam preparation or the future value of the current investment decision can increase
- Potential mechanisms:

1. Candidates compensated for the drop in vacancies by increasing effort
2. The hiring freeze disrupted candidates' process for learning about their own ability
3. The length of hiring freeze was uncertain, so candidates chose to remain competitive when the hiring freeze ended

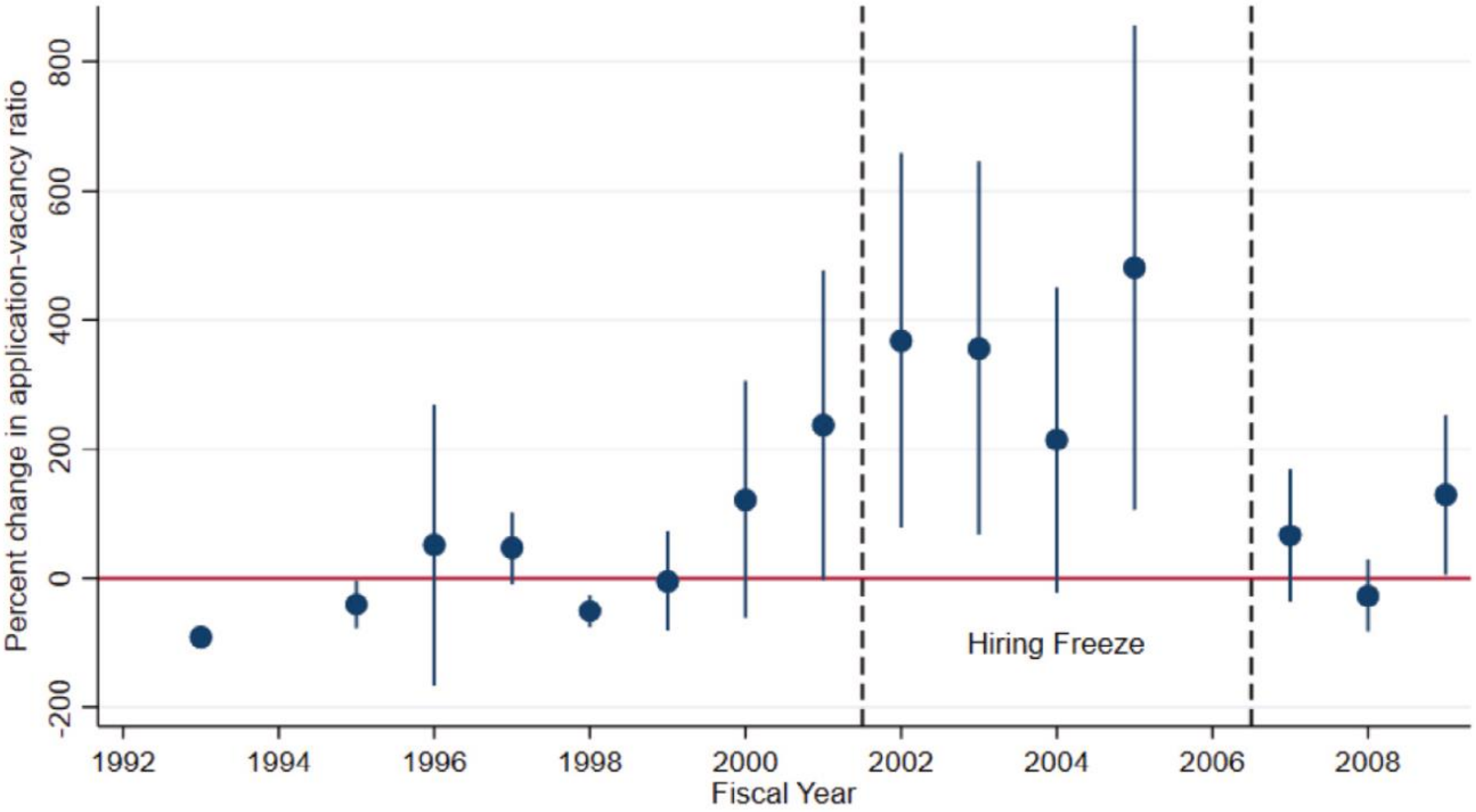
1: The impact on application behavior

- Data: Information on recruitment notifications, digitized from annual Tamil Nadu Public Service Comission (TNPSC) reports from 1992/93 to 2009/2010 fiscal year
- Empirical strategy: Pre-post design
- **72% fewer vacancies** were offered within the specific subset of posts that were notified during the hiring freeze
- **No significant effect on applications**

-> **390% more applications per vacancy**

1: The impact on application behavior

(c) Application-Vacancy Ratio



Empirical strategy

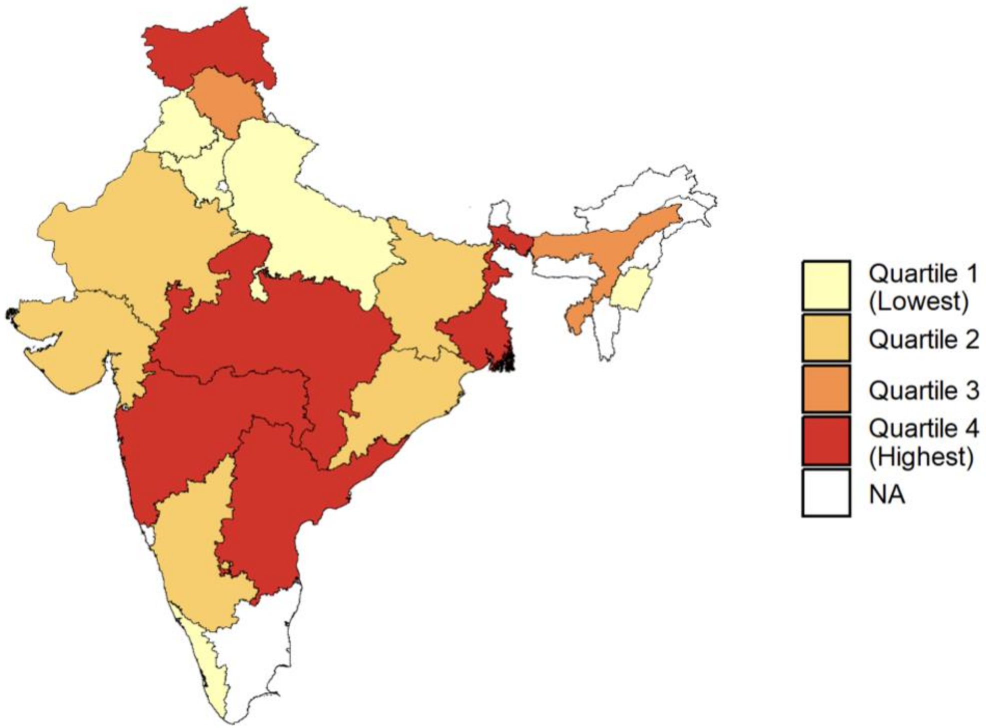
- Data: The National Sample Survey (NSS) 1993/94-2005/06
  - Repeated cross-sectional data
  - Outcome variable: Employment status
- Identification strategy: Synthetic DiD
  - Sample: Male college graduates between ages 20-24
  - Specification:
  $$y_i = \beta\left[TN_{s(i)} \times Freeze_{t(i)}\right] + \zeta_{s(i)} + \eta_{t(i)} + \Gamma_0' X_i + \Gamma_1'\left[TN_{s(i)} \times X_i\right] + \epsilon_i$$
  - Captures changes in the rate at which young graduates enter employment across successive cohorts

Empirical strategy

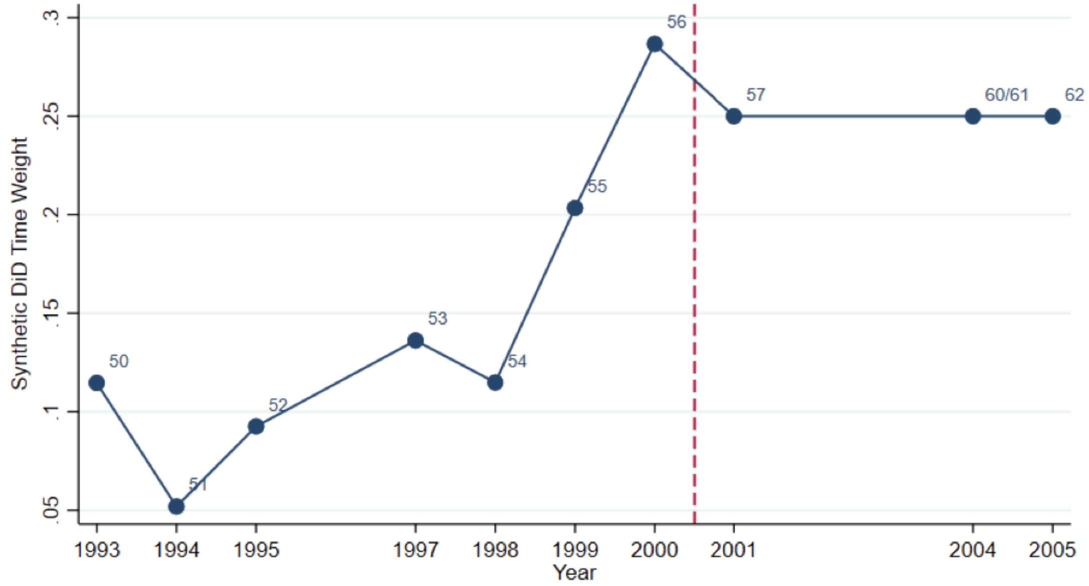
- Implementation of SDiD
  1. Residualize the outcome on the control variables in the specification of interest
  2. Estimate the unit and time period weights, ω_s and λ_t, based on the residualized values following Arkhangelsky et al. (2021)
  3. Estimate the regression parameters weighting observations by $\omega_s \times \lambda_t$
- Standard errors using the jackknife estimator, clustered at the state-by-cohort level; which are valid as long as…
  1. Treatment assignment varies across cohorts
  2. Potential outcomes are independent across cohorts

Empirical strategy

(a) State Weights



(b) Time Weights



2. Contemporaneous impacts on labor supply

Table 2
Contemporaneous impacts of the hiring freeze on labor supply.
Data Source: National Sample Survey, 50th to 62nd rounds (1993/94–2005/06).

			Out of the labor force	
	(1) Employed	(2) Unemployed	(3) Higher education	(4) Other
TN × Freeze	−0.079***	0.039	0.024	0.002
	(0.028)	(0.045)	(0.032)	(0.006)
Mean, TN before freeze	0.464	0.197	0.322	0.017
Observations	17,471	17,471	17,471	17,471

- 19,000 fewer young male college graduates employed per year
- A drop in employment that is 11 times larger than the number of vacancies lost per year

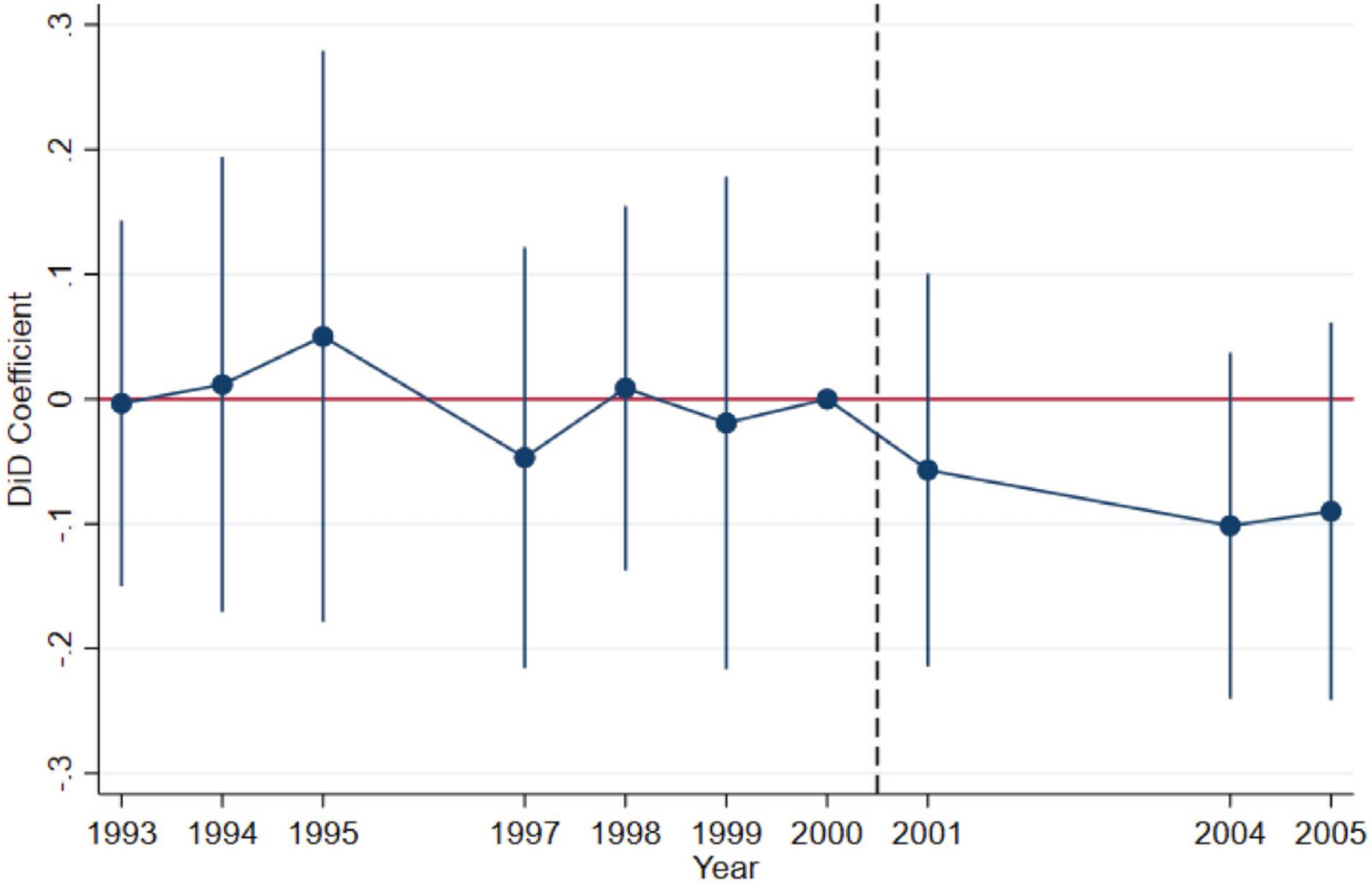
Robustness check: Validity of the counterfactual

- Specification:

$$y_i = \sum_{T(i)} \left[\beta_{T(i)} \times TN_{s(i)}\right] + \zeta_{s(i)} + \eta_{t(i)} + \Gamma_0' X_i + \Gamma_1' \left[TN_{s(i)} \times X_i\right] + \epsilon_i$$

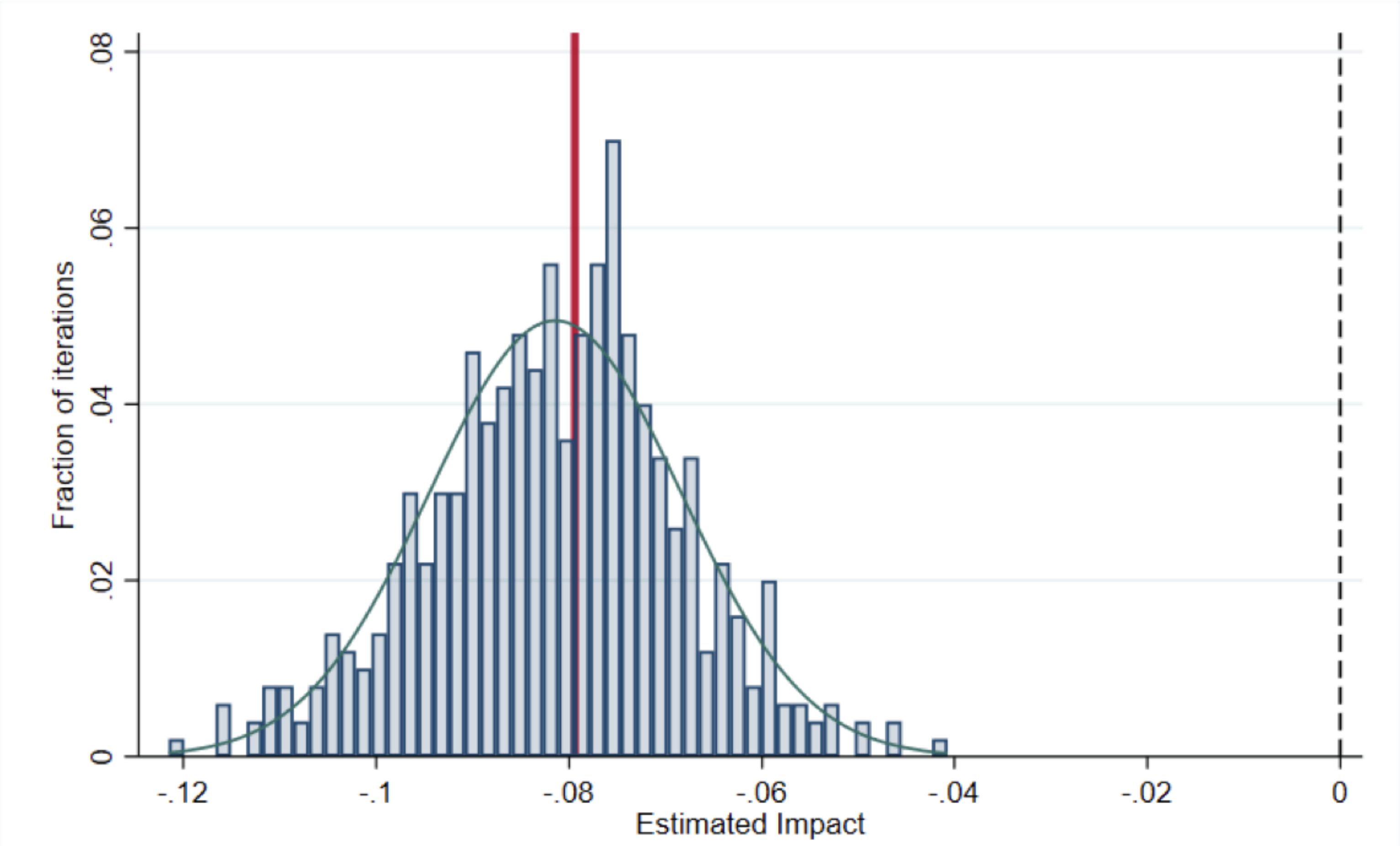
- Checking “pre-trend”
    - cf. Roth, 2022 AER Insights; Rambachan and Roth, 2023 REStud

Robustness check: Validity of the counterfactual



Robustness check: Validity of the counterfactual

Figure A.8: Contemporaneous Impact on Employment: Sensitivity to the Choice of Comparison States



Robustness check: Relevance of other contemporaneous shocks

- Impacts are unusually concentrated on the population that is most likely to apply for government jobs
  - Effect heterogeneity between eligible and ineligible population (by education level)
  - Effect heterogeneity between high (low) exposure groups (by cohorts)
- The impact of the hiring freeze on wage rates: Help to rule out potential aggregate labor demand shock in Tamil Nadu that coincides the policy and confirm labor supply change

Robustness check: Relevance of other contemporaneous shocks

Table 3
Contemporaneous impacts of the hiring freeze on labor supply: Heterogeneity by exposure to the freeze.
Data Source: National Sample Survey, 50th to 62nd rounds (1993/94–2005/06).

			Out of the labor force	
	(1) Employed	(2) Unemployed	(3) Education	(4) Other
Panel A: Variation in eligibility				
TN × Freeze × Eligible (β_1)	−0.082***	0.029	0.023	0.004
	(0.030)	(0.047)	(0.034)	(0.007)
TN × Freeze × Ineligible (β_2)	0.010	−0.008	−0.004	0.003
	(0.012)	(0.008)	(0.003)	(0.006)
$\beta_1 = \beta_2$ p-value	0.000	0.451	0.435	0.953
Mean, TN before Freeze	0.855	0.063	0.056	0.026
Observations	115,093	115,093	115,093	115,093
Panel B: Variation in exposure by cohort				
TN × Freeze × High Exposure Cohort (β_1)	−0.104***	0.055	0.036	−0.003
	(0.038)	(0.036)	(0.028)	(0.008)
TN × Freeze × Low Exposure Cohort (β_2)	−0.019	0.036	−0.035	−0.000
	(0.049)	(0.035)	(0.045)	(0.007)
$\beta_1 = \beta_2$ p-value	0.068	0.704	0.143	0.792
Mean, TN before Freeze	0.556	0.185	0.246	0.012
Observations	27,546	27,546	27,546	27,546

Robustness check: Relevance of other contemporaneous shocks

Table 4
Contemporaneous impacts of the hiring freeze on wage rates.
Data Source: National Sample Survey, 50th, 55th, 60th, 61st, and 62nd rounds.

	(1) Real wages	(2) Log real wages	(3) Not employed in wage labor in the prior week
Panel A: All education groups			
TN × Freeze	0.961	−0.013	−0.027
	(1.918)	(0.039)	(0.021)
Mean, TN before 2001	45.471	3.617	0.299
Observations	33,796	32,436	106,852
Panel B: College graduates			
TN × Freeze	30.450*	0.270	−0.091**
	(18.154)	(0.226)	(0.042)
Mean, TN before freeze	79.451	4.095	0.194
Observations	1,675	1,604	10,164
Panel C: School graduates			
TN × Freeze	1.139	−0.031	−0.029
	(4.470)	(0.071)	(0.031)
Mean, TN before freeze	53.189	3.780	0.267
Observations	8,009	7,714	40,516
Panel D: Ineligible sample			
TN × Freeze	−0.853	0.014	−0.019
	(2.660)	(0.032)	(0.027)
Mean, TN before freeze	40.493	3.528	0.335
Observations	24,087	23,081	56,172

3. Long-run impacts

- Data: Consumer Pyramids Household Survey (CPHS) 2014-2019
  - Panel data, 160,000 households, every four months
  - Outcome variable: Attainment of government jobs, occupational choice in the private sector, income and expenditure, household labor supply, household formation
- Identification strategy: Synthetic DiD
  - Sample: Male college graduates
  - Use variation in exposure to the hiring freeze across cohorts to identify a comparison group
  - Dealing with attrition bias

3. Long-run impacts

Table 5
Long-run impacts.
Data Source: Consumer Pyramids Household Survey, 2014–2019.

	TN × High Exposure (β_1)	TN × Low Exposure (β_2)	p-value $\beta_1 = \beta_2$	Mean	Individuals	Obs.
Panel A: Attainment of government jobs						
Has Govt Job: Any	−0.052**	−0.023	0.251	0.192	14,952	72,087
	(0.025)	(0.028)				
Has Govt Job: Exempted post	−0.017	0.008	0.353	0.071	14,952	72,087
	(0.013)	(0.026)				
Panel B: Occupational choice in the private sector						
Employee	0.048	0.029	0.673	0.437	14,952	72,087
	(0.047)	(0.032)				
Business	−0.110***	−0.107***	0.940	0.307	14,952	72,087
	(0.028)	(0.032)				
Farmer	−0.003	−0.007	0.849	0.018	14,952	72,087
	(0.020)	(0.016)				
Daily wage labor	0.002	0.013	0.559	0.036	14,952	72,087
	(0.013)	(0.017)				
Unoccupied	0.019*	0.007	0.248	0.010	14,952	72,087
	(0.010)	(0.005)				

3. Long-run impacts

Table 5
Long-run impacts.
Data Source: Consumer Pyramids Household Survey, 2014–2019.

	TN × High Exposure (β_1)	TN × Low Exposure (β_2)	p-value $\beta_1 = \beta_2$	Mean	Individuals	Obs.
Panel C: Income and expenditure						
Log labor income	0.021 (0.033)	0.039 (0.031)	0.577	9.825	28,134	940,270
Log total HH expenditure	−0.061*** (0.019)	−0.000 (0.016)	0.000	9.434	37,520	1,434,193
Log expenditure per earning member	−0.096** (0.047)	−0.041 (0.051)	0.032	9.167	37,429	1,418,208
Panel D: Household labor supply						
# other adults in HH	0.360*** (0.131)	0.323* (0.171)	0.804	3.097	23,449	229,106
# other employed HH members	0.147*** (0.042)	0.054 (0.051)	0.081	0.299	18,607	143,385
Fraction other adults employed	0.033* (0.018)	0.007 (0.018)	0.101	0.110	18,557	142,688
Fraction HH members 55+ employed	0.070*** (0.019)	0.030 (0.019)	0.078	0.025	8,198	53,322
Panel E: Household formation						
Head of Household	−0.113** (0.045)	−0.056 (0.060)	0.424	0.813	23,449	229,106
Married	−0.087*** (0.020)	−0.024 (0.029)	0.068	0.955	23,237	226,339