Can Effective Policy Implementation Alter Political Selection? Evidence from Female Legislators in India

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Abstract

Can effective policy implementation change political selection by inducing voters to prioritize leader competence over other traits, such as gender? This paper answers this question by examining the impact of a successful school-expansion program on the likelihood of women being elected to state legislatures in India. The paper shows that the program increased voter prioritization of leader competence over gender, boosting the share of women among candidates and state parliamentarians and the overall capability of elected officials. These findings are consistent with the predictions of a model of candidate self-selection where voters trade off candidate competence with their bias against female leaders.

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Can Effective Policy Implementation Alter Political Selection? Evidence from Female Legislators in India*

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1 Introduction

Women are remarkably underrepresented in elected office around the world. As of January 2023, women accounted for only 26.5 percent of national parliament members globally. This gender gap in political leadership is prevalent in nearly all countries; e.g., women comprised 29 percent of the US Congress and 31 percent of the UK Parliament in 2023.[1] In fact, only six countries have 50 percent or more women in parliament. In India, the context of our study, merely 12.2 percent of the national and state legislators in 2021 were female. Besides equity considerations, women's underrepresentation in government has significant welfare implications. Numerous studies have shown that increasing the share of female leaders not only results in more favorable outcomes for women (Beaman et al., 2012; Chattopadhyay and Duflo, 2004; Iyer et al., 2012), but also leads to better development outcomes more broadly (Baskaran et al., 2021; Bhalotra and Clots-Figueras, 2014; Brollo and Troiano, 2016; Clots-Figueras, 2012; Dollar et al., 2001; Miller, 2008; Swamy et al., 2001).

The underrepresentation of women in elected positions can result from multiple factors such as a lower rate of entry into politics and a lower rate of career progression within politics for women (Brown et al., 2020).[2] Even if female politicians are interested in contesting elections, voters may be gender-biased against female candidates and parties may be unwilling to field female candidates due to their lower chances of victory (Le Barbanchon and Sauvagnat, 2022; Sanbonmatsu, 2002; Schwarz and Coppock, 2022; Teele et al., 2018). In majority rule elections when voters trade off gender bias against leader competence, less competent leaders may be elected if voters are sufficiently biased, causing societal welfare loss (Krishna and Morgan, 2011).

We examine whether exposure to well-implemented public policies or programs increases voters' prioritization of politician competence over their gender. Such a re-weighting of voter priorities may occur regardless of whether the effective policies are implemented by male or female leaders (though exposure to effective female leaders may have a larger impact on re-prioritization; Beaman et al. (2009); Bhavnani (2009)). By leading voters to elect more competent men and women in place of less competent men who previously benefited from voters' gender bias, the number of women elected to office may increase following observable effective governance.

To the best of our knowledge, the question of whether competent delivery of public programs can increase women's elected leadership is as yet unanswered. Administrative ca-

[1] Source: Parline Data, Inter-Parliamentary Union (`https://data.ipu.org/`).

[2] For instance, women may have lower ambition (Lawless and Fox, 2010), may lack female role models (Beaman et al., 2009), may be averse to competitive environments (Gneezy et al., 2003), and may face gender stereotypes and opposition from their families, among other things.

pability is something that all elected leaders have the opportunity to exercise in office. Understanding whether the demonstration of this capability can successfully lead voters to prioritize politician competence over politician gender has far-reaching welfare implications.

Specifically, we study whether the District Primary Education Program (DPEP), a large national primary school expansion program in India, impacted women's probability of being elected as members of legislative assemblies (MLAs) at the state level. The DPEP was implemented in a staggered manner during the period 1993-2004 in districts that had female literacy rates below the national average (according to the 1991 Census of India). Central and state governments in concert built new primary schools and trained new teachers in program districts across the country. They also facilitated the creation of local school committees to prioritize community engagement with student learning. At the time of its implementation, the DPEP was the largest program for primary education in the world, in terms of budget, geographical spread, and number of beneficiaries. The DPEP not only improved educational attainment and earnings of its direct beneficiaries (Azam and Saing, 2017; Khanna, 2023), but also indirectly improved learning outcomes of children whose mothers were direct beneficiaries of the DPEP (Sunder, 2020).

To illustrate the channels through which the DPEP potentially altered political outcomes, we develop a probabilistic voting model in the spirit of Dal Bó and Finan (2018). The model captures both the demand and the supply sides of the electoral process: voters face a trade-off between politician competence and their bias in favor of male leaders, and politicians of both genders choose whether or not to contest elections based on their probability of winning.

The scale of the DPEP provided ample opportunity for leaders to demonstrate their competence in its implementation. Moreover, the program explicitly emphasized reductions in gender disparities in access to education and incorporated community awareness initiatives on the importance of girls' education. For these reasons, in our model (we assume that) the DPEP increases voters' marginal utility from leader competence relative to that from having male leaders.[3] As a consequence, the DPEP leads to an increase (decrease) in the threshold level of competence that male (female) politicians must possess to contest elections as voters increasingly prioritize this attribute over their desire for male leadership.

The model delivers five main predictions. First, the DPEP should increase the probability of female candidates winning elections. Second, the DPEP should decrease (increase) the number of men (women) competing in elections. Third, the average quality of male (female) candidates should improve (decline) in DPEP districts relative to non-DPEP districts. As

[3]The change in voters' relative utility in the framework occurs due to either a direct increase in voter utility from leader competence, or a decrease in voter utility from leaders being male, or both these channels acting simultaneously.

the majority of candidates in contested elections tend to be male, the DPEP should lead to an overall increase in the average competence of candidates. Fourth, the effect of the DPEP should be more pronounced in districts where women were elected in previous elections. In these districts, barriers to women's political entry may be lower and voters may be more responsive to the benefits of competent program delivery as opposed to politician gender. Moreover, the DPEP-induced increase in women's probability of winning may have a "demonstration effect" and increase women's candidacy. Fifth, the impact of the DPEP on women's likelihood of being elected should be stronger in districts where the program was most effectively implemented.

To test these predictions, we employ a fuzzy regression discontinuity design that exploits the 1991 Census female literacy rate as a cut-off for district eligibility for the DPEP. We use data on state elections that took place after the DPEP began, with 2018 being the latest election year in our sample. Consistent with our model, we estimate that voters are 22 percentage points (p.p.) or four times more likely to elect female MLAs in treated districts compared to untreated districts. We also find a significant drop-out of marginal male candidates as reflected in the number of independent male candidates who contest without political party affiliation; such candidates have a historically low probability of winning of less than 2 percent. As predicted by the model, we document a 10 percent increase in the number of female contestants due to the DPEP (though this effect is not statistically significant). Notably, the probability that the incumbent party and other parties field a female candidate increases, respectively, by five and nine times in DPEP districts relative to non-DPEP districts if the winner in the previous election was female. While data limitations prevent us from an in-depth analysis of whether the DPEP altered candidate competence, we find that candidates in DPEP districts have a higher rate of secondary school completion, potentially indicative of higher equilibrium competence. These results are broadly consistent with the predictions of our theoretical model.

We provide several pieces of evidence to show that the key mechanism underlying these results is that effective DPEP implementation made leader competence more observable in treated districts, prompting voters to increase the weight that they assigned to candidates' competence relative to their gender. First, we show that the DPEP-driven increase in the probability that women win elections is larger in treated districts where the DPEP led to greater improvements in education infrastructure and performance and in the local economy (as measured by satellite nightlights data). Second, we show that in elections that took place after the DPEP began, voters in treated districts are more likely to re-elect candidates from the incumbent party and candidates that are "unaligned" with the leading party in the state. This pattern of results reflects a marked deviation from historical trends as, in the absence of the DPEP, voters overwhelmingly voted against the incumbent party candidate in their constituency, and voted for the candidate from the party that ultimately wins the most seats in the state.[4] So, the DPEP appears to have reduced voters' inclination to punish the local incumbent party and increased their willingness to sacrifice state patronage to elect an unaligned candidate, who likely will not be part of the state government. Both these deviations from past election outcomes are consistent with increased candidate competence following DPEP implementation.

Regarding whether the DPEP reduced voters' gender bias, we find evidence of some gains to female candidates from this channel as well, but these gains occur only under specific political conditions. We show that voters' desire to vote for or against a political party is the primary determinant of when the gains to female candidates from the DPEP manifest, as it influences when voters' party preferences outweigh their reluctance to vote for women; and that this reluctance is overcome to a higher degree in treated districts. We establish this by investigating whether female candidates win more often in "decisive" elections, where voters greatly desire to elect their preferred parties and winning margins are wide in seats across the state (a political environment where candidate gender is less likely to matter to voters than party affiliation). We find that the increased win probability for women due to the DPEP manifests *exclusively* in such decisive elections, and also *only* when female candidates are aligned with the leading party in the state. Hence, while the DPEP does appear to have reduced voters' bias against female leaders, the intensity of voters' preferences over which party should govern the state, and their perceived patronage gains from electing women, are the dominant factors determining when they exercise this reduced bias.

We conclude our paper by showing that our results are unlikely to be driven by an obvious alternative mechanism, namely the increase in educational attainment of residents in DPEP districts. The effect of the DPEP on the probability that women win manifests shortly after the DPEP begins (within the first seven years of program implementation). The timing of the effect cannot be explained by the DPEP-led increase in educational attainment of voters and candidates because directly treated primary-age cohorts would nearly all be below the minimum age for voting and for contesting MLA elections during the first seven years of the program. Nevertheless, the positive impact of the DPEP on the likelihood of female candidates winning MLA elections persists even eight years and further beyond the start

[4] Existing evidence attributes voters' anti-incumbency to their dissatisfaction with the ruling party's performance (Klašnja and Titiunik, 2017; Uppal, 2009). Voters' propensity to elect the candidate aligned with the leading party in the state, which likely forms the state government on its own or in coalition with other parties, is ostensibly attributable to associated patronage benefits, which governments provide to loyal constituencies in various forms such as transfers, public expenditure, and facilitating local industry (Asher and Novosad, 2017).

of the program in treated districts, indicating a long-term increase in voters' willingness to elect women.

Our paper contributes to the growing literature in economics and political science on political selection (Le Barbanchon and Sauvagnat, 2022; Dal Bó and Finan, 2018; Gulzar, 2021; Gulzar and Khan, 2021; Mansour et al., 2020). Our findings constitute the first set of evidence that large state programs that provide the opportunity for leaders to demonstrate their competence can increase women's elected representation when voters are gender-biased. Our study suggests that women's political representation in India, and perhaps other parts of the world, can increase organically with voter prioritization of leader competence over leader gender when they benefit from public policy measures. These findings are especially important given the large literature showing that the characteristics of elected representatives matter for policy outcomes (Besley et al., 2011; Chattopadhyay and Duflo, 2004; Clots-Figueras, 2012).

Our paper is also directly related to the vast literature on women's political representation, especially in India. Previous research has exploited quasi-random quotas for women introduced in elected village council seats and headships (Beaman et al., 2012, 2009; Chattopadhyay and Duflo, 2004; Iyer et al., 2012; O'Connell, 2018, 2020), or close elections between men and women that generate quasi-random variation in the gender of the winner (Bhalotra and Clots-Figueras, 2014; Bhalotra et al., 2018; Clots-Figueras, 2012). However, these are specific conditions that do not apply to the majority of political offices in India or other countries. Our findings on the impact of a large public program on voters' propensity to elect women instead apply to a far wider context. Moreover, unlike supply-side quotas, our study is focused on the demand side of political selection to boost women's elected representation.

2 Background

In this section, we provide background information on the DPEP, on state elections in India, and on women's representation in Indian politics.

2.1 The District Primary Education Program

The District Primary Education Program (DPEP) began in 1993, and was implemented in a staggered manner in 219 (248 bifurcated districts) of India's 593 districts across 18 states by the time it was phased out in 2004. The program aimed to achieve universal primary education and to improve learning outcomes through school construction, improvements in school infrastructure, textbook development, and teacher training. The program explicitly emphasized reductions in disparities in access for girls and children from disadvantaged communities, including the Scheduled Castes (SC) and Scheduled Tribes (ST). Additionally, the DPEP sought to strengthen state capacity and encouraged the formation of Village Education Committees and other local bodies to mobilize communities and raise awareness of the importance of primary education for all children, among other things. Decentralization and local empowerment were much emphasized components of program delivery, alongside the prioritization of student learning (Pandey, 2000).

Districts with female literacy rates below the national average of 39.3 percent in the 1991 Census of India were designated as program eligible. The DPEP was rolled out in a phased manner, with 42 districts receiving the program in Phase-1 (1994-2001), 80 districts receiving the program in Phase-2 (1996-2002), 27 districts receiving the program in Phase-3 (1998-2003), and the remaining 70 districts receiving the program in subsequent phases that began in 1999-2000 (Azam and Saing, 2017). The program was implemented at a large scale with total funding of USD 1,317 million. The central Government of India bore 85 percent of program expenditure, aided by international donors such as the World Bank and the UK Department for International Development; state governments bore the remaining 15 percent. To ensure that resources at the state level were not substituted away from existing education budgets, the central government stipulated that these budgets were to remain unchanged, thus creating a large DPEP-induced increase in government education expenditure (Sunder, 2020).

The DPEP facilitated the construction of more than 160,000 schools and the training of 1.1 million teachers, and increased funds for primary school education by between 17 percent and 20 percent (Azam and Saing, 2017). Approximately 51.3 million children benefited from the program's infrastructural and administrative expansions (Jalan and Glinksya, 2013).

2.2 State Elections in India

Elections to state legislatures in India are held every five years for each state. Candidates contest in first-past-the-post elections in constituencies (or seats) across each state, and winners are appointed as MLAs in the state. The political party, or a coalition of parties, with a simple majority of MLAs in the assembly forms the government in the state with the assent of the Governor of the state. The state government then serves a five-year term, unless the assembly is dissolved by the Governor in exceptional circumstances. A new party or coalition can govern for the remainder of the five-year term in such cases, but an election is again held once the term ends. Ruling MLAs from the governing party or coalition wield substantial power; they can hold ministerial positions, spend budgetary resources in their constituencies, and pass state-level legislation. The years in which state elections are held are decided according to rules set out in the Constitution of India, and cannot be changed by the national government or state governments.

2.3 Women's Representation in Indian Politics

Members of the national parliament and state legislative assemblies in India are overwhelmingly men. Women's underrepresentation arises from patriarchal societal norms that limit women's agency and participation in public spaces, and make voters gender-biased in favor of male candidates. Consequently, gender-unequal outcomes prevail not just in politics, but also in other spheres, such as health, education, labor force participation, freedom of movement, and property rights. To tackle women's political underrepresentation, the Indian government mandated quotas for women in village councils and urban bodies through the 73rd and 74th Amendment Act of 1992. After the passage of the Act, one-third of all council seats and council headships are reserved for women when council elections take place in any state in India. Studies have shown that these gender quotas reduce voter bias against female leaders over time after initial backlash (Beaman et al., 2009), create a pipeline of experienced women candidates who contest elections at higher levels of government (O'Connell, 2020), increase the aspirations of girls exposed to their leadership via role-model effects (Beaman et al., 2012), and improve women's participation in the labor market (Ghani et al., 2014) and female entrepreneurship (Mani and O'Connell, 2019). However, as there are no reservations for women at the state or the national level, alternative paths to ameliorating their underrepresentation in state and national parliaments merit investigation.

3 Theoretical Framework

We adapt the theoretical model in Dal Bó and Finan (2018) to outline the channels through which the DPEP potentially alters voters' preferences in favor of candidates' competence relative to their gender, and also affects politicians' decisions to contest. Dal Bó and Finan (2018) set out a probabilistic voting model with candidates from two rival political groups, where voters trade off candidates' competence with partisan alignment and candidates self-select into running for electoral office. Our model recasts party alignment into gender bias, so that voters trade-off candidates' competence with their bias in favor of electing male leaders.[5] The model generates testable predictions on candidates' decisions to contest elections as well as voters' choices.

[5] An analogous model can be used to analyze other types of biases, such as those based on ethnicity, religion, or caste.

3.1 Model Setup

We assume that in each election there are two groups of possibly gender-biased voters. Voters of type m prefer male leaders while voters of type f prefer female leaders. The two groups of voters measure $\rho \in (0,1)$ and $(1-\rho)$, respectively.[6] Voters elect a single leader in a first-past-the-post election setting from the two groups of candidates, each with measure one. For simplicity, we assume that parties decide to field the candidates that are most likely to win the elections, but otherwise abstract from considerations about party governance and candidate selection. Given the focus of our analysis, we model the case in which there are two candidates competing for election and these two candidates are of different genders.[7]

Candidates vary not only in their gender, but also in their quality. Specifically, each candidate has a specific trait v_j which we refer to as "competence." Competence is drawn from uniform distributions in the range $[0, \bar{v}_j]$ with $j = m, f$, allowing male and female candidates to have differing competence ranges. Thus, a candidate's type is given by the pair (v_j, j), where j denotes the candidate's gender. We assume that candidate type is visible to voters at the time of the elections.

A voter i receives a benefit from electing a leader of type (v_j, j) given by:

$$\bar{\omega} v_j \, + \, I(j)\delta_i$$

where $\bar{\omega} > 0$ measures how voters weigh candidate competence relative to gender. The indicator function $I(j)$ equals one if $j = m$ and equals zero otherwise, providing a utility gain from male-bias for m-type voters. The parameter δ_i measures the idiosyncratic bias of voter i for a male candidate, and is distributed uniformly over $[\phi - \frac{1}{2}M, \phi + \frac{1}{2}M]$ among m voters, and over $[-\phi - \frac{1}{2}F, -\phi + \frac{1}{2}F]$ among f voters. Thus, ϕ captures the preference distance between m and f voters or the societal division over attitudes to leader gender. We assume that $\phi > 0$ which implies that, in the absence of competence differences, m-type voters will tend to support male candidates, while f-type voters will prefer female candidates. We also assume that $\phi - \frac{1}{2}M < 0$ and $-\phi + \frac{1}{2}F > 0$ to allow for the possibility that some m-type voters could vote for a female candidate and that some f-type voters may support a male candidate. This implies the presence of some "swing voters," who could be influenced even by small competence differentials between candidates. The parameters $M, F > 0$ also denote the importance of gender for a voter's political preference, somewhat capturing group cohesion.

[6] One could assume that female voters tend to prefer female leaders while male voters prefer male leaders, though this is not required by our model.

[7] An extension to a model where voters care both about party affiliation and leaders' gender is straightforward but does not add much to our analysis.

Once each party has recognized its potential candidate, candidate competence is realized and each candidate privately learns about their own competence. Then, each candidate makes a decision on whether to enter the competition, facing uncertainty about the competence of their opponent. In the event that no one chooses to run, the parties re-draw their candidates. Should one single individual decide to run, they automatically emerge as the winner. If both candidates choose to run, an election takes place. The candidates' competence as well as δ_i become observable to voters just before the election takes place. The winner collects their payoff after the election and the loser receives a payoff of zero.

A candidate of type (v_j, j) will run if and only if the expected private benefit from running is non-negative:

$$P(j \text{ wins})b - k \geq 0$$

where b is the benefit from office and k is the cost of running. For simplicity, we assume that the benefit from office and the cost of running do not vary with competence and they are the same for both candidates. We also normalize the cost of running to one, i.e. $k = 1$.[8]

A voter i chooses a male candidate if and only if the benefit from electing a male leader, $\bar{\omega} v_m + \delta_i$, is higher than the benefit from electing a female leader, $\bar{\omega} v_f$, i.e.,

$$\delta_i \geq \bar{\omega}(v_f - v_m).$$

This yields the following vote shares for the male and female candidates, respectively:

$$s_m = \frac{1}{2} + [\rho M + (1-\rho)F]\bar{\omega}(v_m - v_f) + [\rho M - (1-\rho)F]\phi \tag{1}$$

and

$$s_f = \frac{1}{2} - [\rho M + (1-\rho)F]\bar{\omega}(v_m - v_f) - [\rho M - (1-\rho)F]\phi. \tag{2}$$

The male candidate's vote share increases (and the female candidate's share decreases) with the distance between groups, ϕ, whenever men have, as in the Indian context, an electoral advantage (i.e., whenever $\rho M > (1-\rho)F$). Since $\phi > 0$, higher M and F make gender a stronger determinant of the vote relative to competence.

The female candidate wins against her male competitor if and only if $s_f - s_m > 0$, or:

$$v_f - v_m > \frac{\phi}{\bar{\omega}} \left\{ \frac{\rho M - (1-\rho)F}{\rho M + (1-\rho)F} \right\}. \tag{3}$$

Turning again to the candidates' decision to run, candidate j will run based on whether

[8]See Dal Bó and Finan (2018) for an alternate model where k varies with v_j.

the other candidate runs and their expected benefits from that contest. A female candidate runs if and only if:

$$\frac{b-1}{b} \geq P(m\,\text{runs})P\left(s_f < \frac{1}{2}|v_f\right). \tag{4}$$

Analogously, a male candidate runs if and only if:

$$\frac{b-1}{b} \geq P(f\,\text{runs})P\left(s_m < \frac{1}{2}|v_m\right). \tag{5}$$

In other words, the net benefit from holding office has to exceed the risk of defeat for each candidate. Because a candidate's competence is private information, the probability that the opponent runs does not depend on it. In essence, candidates with high competence tend to be more confident about winning and thus are more inclined to bear the cost associated with running. Moreover, the likelihood of a candidate losing the election decreases as their competence level rises.

Under the assumptions detailed above, it is possible to show that, if an equilibrium exists, it is unique, and the following proposition holds (Dal Bó and Finan, 2018):

Proposition 1. *Define* $x = \frac{\phi}{\omega}\left\{\frac{\rho M-(1-\rho)F}{\rho M+(1-\rho)F}\right\}$. *In equilibrium, the relatively high-competence candidates will run for office. Candidates of each gender will run if and only if their competence exceeds the following gender-specific thresholds:*

$$v_f^* = max\left\{0, min\left\{\frac{\bar{v}_m}{b} + x, \bar{v}_f\right\}\right\}, \tag{6}$$

$$v_m^* = max\left\{0, min\left\{\frac{\bar{v}_f}{b} - x, \bar{v}_m\right\}\right\}. \tag{7}$$

.

Note that, when gender asymmetries arise only from men's electoral advantage due to their gender rather than underlying differences in competence between male and female candidates (i.e., when $\bar{v}_m = \bar{v}_f = \bar{v}$), female candidates have higher quality on average (i.e., $v_m^* > 0$ and $v_f^* \geq v_m^*$).

3.2 Testable Predictions

Proposition 1 shows that the interior equilibrium cutoffs are given by a combination of supply-side parameters ($\frac{\bar{v}_j}{b}$) and demand-side parameters (summarized by x). Note that the strategies for male and female candidates are the same if the demand-side term x goes to zero. Also note that a decline in x would reduce the competence differential between female and male candidates required for a female candidate to win an election, resulting in an overall increase in women's probability of being elected. The larger is the decline in x, the higher the likelihood of an elected female candidate.

We argue that the DPEP may impact political selection through multiple demand-side channels.[9] First, the program may increase $\bar{\omega}$ (the weight that voters give to competence) as voters experience the benefits of competent delivery of the program, such as better education for their children and increased economic growth from local investment of program resources. Second, the DPEP may decrease ϕ (the degree of polarization around voters' gender preferences) by providing voters with gender awareness education and potentially exposing them to competent female leaders involved in program delivery. Third, the program could decrease ρ (the share of male-biased voters). Fourth, the program could reduce voters' gender bias directly through changes in M and F (our measures of group cohesion), essentially altering the margin of swing voters. Crucially, as long as x is positive (i.e., for high enough values of ρ, which we expect to be the case in the Indian context) women candidates still need to have greater competence than their male competitors to overcome voters' gender bias and be elected. Empirically, this competence differential can lead to potentially large increases in the probability of women being elected in DPEP districts only once voters observe women officials being demonstratively more competent and productive than the male officials elected previously.

In summary, our model delivers the following five testable predictions:

Prediction 1. The DPEP increases the probability of female candidates winning elections.

Prediction 2. The DPEP increases the probability of women competing in an election. This can stem from the dropout of low-competence male candidates, the increase in the number of female candidates, or both.

Prediction 3. The average quality of male (female) candidates improves (declines) in DPEP districts relative to non-DPEP districts. As the majority of electoral candidates are male, the DPEP leads to an overall increase in average candidate competence.

Prediction 4. The effect of the DPEP on women's likelihood of being elected is stronger in districts where women were elected in previous elections.

Prediction 5. The effect of the DPEP on women's likelihood of being elected is stronger in districts where the DPEP was most effectively implemented.

[9]Supply-side effects are also possible, but less likely. It is not obvious how the DPEP would directly change the benefit from holding office. As we discuss in Section 7.4, the DPEP is also unlikely to change the distribution of candidate competence in the short to medium-run (which is our horizon of interest).

Note that while Predictions 1 to 3 follow from the overall decline in the electoral asymmetry term x following the implementation of the DPEP, Predictions 4 and 5 more specifically point to the mechanisms behind such a decline. In Section 6, we discuss our empirical results, which we present in the order in which the model predictions are introduced above. In Section 7, we further explore the mechanisms through which the DPEP impacted political selection.

4 Data

Our data on DPEP implementation comes from Government of India reports, supplemented with information from other studies on the program; e.g., Azam and Saing (2017); Khanna (2023); Pandey (2000); Sunder (2020). We combine this data with electoral constituency (or seat) level data on state election outcomes from the Socioeconomic High-resolution Rural-Urban Geographic data set for India (SHRUG) created and made available for public use by the Development Data Lab (Asher and Novosad, 2017). The SHRUG data set contains detailed information on several economic, environmental, and political aggregates at a local geographic level, including constituency-level state election information relevant for our analysis (the number of contesting candidates in each seat, candidates' gender and political affiliations, and vote shares for each candidate). We make use of this electoral data for all state elections that took place in India during the period 1974-2018. We also utilize satellite data on district-level night-time luminosity from SHRUG (Asher et al., 2021) to estimate the impact of the DPEP on economic growth, for which night-time lights data has been used as a proxy measure in previous studies (Henderson et al., 2012; Prakash et al., 2019; Storeygard, 2016).

To measure heterogeneity in the effectiveness of DPEP implementation in improving school infrastructure and children's engagement with primary education, we use data from India's District Information System for Education (DISE) from the year 2004-05 (the first post-DPEP year for which the data are available). The DISE data are collected annually, and contain detailed information from all districts in India on school construction and infrastructure availability as well as on measures of student participation and the number of students appearing for exams. We use this data to construct an index of district-level educational performance that incorporates infrastructural inputs and student engagement measures, and investigate whether more female MLAs are elected in districts where the DPEP increased educational performance more effectively.

In addition, we utilize original candidate affidavits data provided by the Association for Democratic Reforms to estimate whether the DPEP had any impact on the composition of the pool of candidates. The data contains candidate declarations of their characteristics such as their education level, assets, and whether they have been accused of any crimes. A shortcoming of this affidavit data is that it is only available for post-DPEP years (2004-2018).

Finally, we utilize data from the 1991 Census of India to compare districts that were eligible for the DPEP treatment with districts that were ineligible.

4.1 Descriptive Statistics

In Table 1, we present some descriptive statistics on constituency-level state election outcomes during 1974-2018, and also on candidate characteristics for elections during 2004-2018. We report these statistics for districts that lie within a 12-point female literacy rate bandwidth of 39.3 percent in the 1991 Census, as this is the approximate optimal bandwidth in our main estimates.

Panel A reports the statistics for election data aggregated at the district-by-year level. An average seat is contested by ten candidates, and these candidates are overwhelmingly male (with only 0.5 female candidates per seat, on average). Roughly half of the contesting candidates are affiliated to a political party, and the other half are independents. Not all candidates are competitive, however, as the "effective" number of parties per constituency on average is only three, suggesting that a large fraction of the candidates, who are largely male, are marginal to the electoral contest.[10] The low rate of entry of female candidates is also visible in the share of elections with at least one female candidate, which is only 0.34. Female candidates also have only a 5 percent chance of winning a constituency. Candidates that win a constituency are aligned with the leading party in the state in 57 percent of elections and only 30 percent of winners are from the incumbent party in power in that constituency.

Panel B shows that 93 percent of contesting candidates have completed primary school, and 78 percent of them have completed secondary school. These completion rates are broadly comparable to the primary and secondary school completion rates in the Indian population of 94 percent and 85 percent, respectively, in 2017 (UNESCO Institute for Statistics). However, contesting candidates are significantly wealthier than the average population, with declared assets of INR 20.38 million per candidate on average. In contrast, per capita net national income in India was substantially lower at INR 1,26,406 during 2018-19.[11] Contesting candidates also have a high rate of criminality, with 16 percent of candidates having been accused of a criminal case, and 8 percent of candidates facing serious charges such as murder, kidnapping, or arson.

[10]The effective number of candidates is calculated as the inverse of the sum of squares of each candidate's vote share.

[11]This income estimate is from the Ministry of Statistics and Program Implementation in India, available at `https://shorturl.at/CEIU1`.

Table 1: Descriptive Statistics

	Observations	**Mean**	**S.D.**	**Min**	**Max**
Panel A: Election Outcomes	(1)	(2)	(3)	(4)	(5)
Total no. of candidates	9,200	10.36	7.26	1	301
Effective number of parties	9,197	2.92	0.97	1.05	12.50
No. of female candidates	9,200	0.49	0.94	0	49
No. of male candidates	9,200	9.87	6.83	1	252
No. of independent candidates	9,200	5.30	6.22	0	298
No. of parties	9,200	5.03	2.61	0	24
Constituencies with $\geq$ one female candidate	9,200	0.34	-	0	1
Female winner	9,200	0.05	-	0	1
Aligned winner	9,200	0.57	-	0	1
Winner from incumbent party	9,200	0.30	-	0	1
Panel B: Candidate Characteristics	(1)	(2)	(3)	(4)	(5)
Completed primary schooling	33,895	0.93	-	0	1
Completed secondary schooling	33,895	0.78	-	0	1
Accused in criminal case	35,033	0.16	-	0	1
Accused in serious criminal case	35,033	0.08	-	0	1
Total declared assets (INR in millions)	35,033	20.38	-	0	10,205

Notes: Panel A shows descriptive statistics for variables from the SHRUG dataset on district$\times$year-level state election outcomes during 1974 to 2018. Panel B shows descriptive statistics from affidavit data provided by the Association of Democratic Reforms on candidate characteristics for state elections during 2004 to 2018.

5 Empirical Strategy

To test the model predictions and study the DPEP's impacts on political outcomes, we adopt a fuzzy regression discontinuity design (hereafter RDD; Hahn et al. (2001)) and estimate a non-parametric local linear regression using a selected bandwidth of data around the cut-off. For optimal bandwidth selection, we use the Calonico et al. (2019) procedure. As mentioned earlier, districts that had a female literacy rate below the national average (39.3 percent) based on the 1991 Census of India were targeted by the DPEP. However, not all eligible districts were treated, yielding a fuzzy RDD based on the 1991 district female literacy rate as the running variable. Figure 1 clearly shows a sharp increase in treatment probability for districts with female literacy rates just below the eligibility threshold. However, it also shows that many eligible districts remained untreated, and some ineligible districts received treatment. Nevertheless, the discontinuous change in treatment probability at the eligibility cut-off provides a suitable setting for our chosen methodology and allows us to causally estimate the local average treatment effect (LATE) for districts near the cutoff (Imbens and Angrist, 1994). Figures 2(a)-2(f) in the Appendix show that there were no other discontinuities around the same cut-off in terms of the following 1991 district-level characteristics: employment rate, share of Scheduled Caste (SC) population, male-female sex ratio, number of primary schools per capita in the average village, and the share of villages that have paved roads and post offices. These figures further support the validity of our fuzzy RDD estimation strategy.[12]

We implement the augmented procedure in Calonico et al. (2019) that permits the inclusion of additional covariates and inference using bias-corrected cluster-robust standard errors. Let the cut-off be denoted by c, and the DPEP treatment assignment rule for district i be $T_i = \mathbb{1}(X_i < c)$, where X_i denotes district i's female literacy rate in 1991. Further, let D_i be the observed treatment status of district i. For outcome of interest, Y_i, assuming perfect district compliance with the treatment assignment criteria, the impact of the DPEP can be estimated by fitting the weighted least squares regressions of Y_i on X_i above and below c using the sample of n districts:

$$\hat{\boldsymbol{\beta}}_- = arg \min_{b_0, b_1} \sum_{i=1}^{n} \mathbb{1}(X_i < c)(Y_i - b_0 - b_1(X_i - c))^2 K\left(\frac{X_i - c}{h}\right) \tag{8}$$

and,

$$\hat{\boldsymbol{\beta}}_+ = arg \min_{b_0, b_1} \sum_{i=1}^{n} \mathbb{1}(X_i \geq c)(Y_i - b_0 - b_1(X_i - c))^2 K\left(\frac{X_i - c}{h}\right) \tag{9}$$

where $\hat{\boldsymbol{\beta}}_- = (\hat{\beta}_{-,0}, \hat{\beta}_{-,1})$ and $\hat{\boldsymbol{\beta}}_+ = (\hat{\beta}_{+,0}, \hat{\beta}_{+,1})$; $K(.)$ is the triangular kernel function, and h is the mean squared error optimal bandwidth as computed in Calonico et al. (2019).

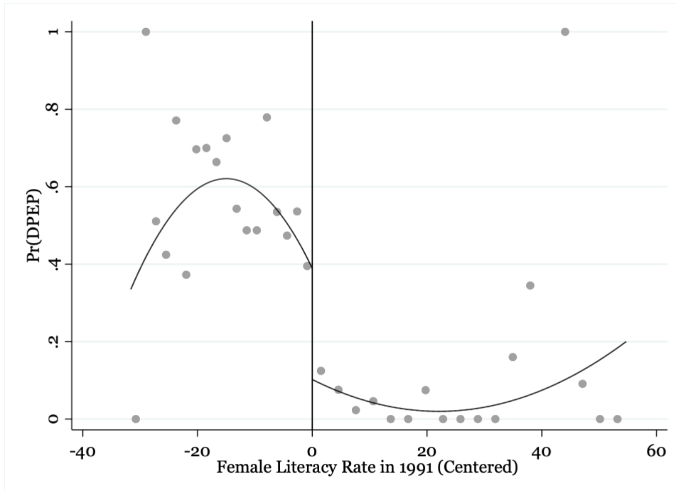
Assuming perfect compliance, the sharp RDD estimator of the DPEP's impact on Y_i is then the difference between the estimated intercepts, or $\hat{\tau}_{SRD}(h) = \hat{\beta}_{-,0} - \hat{\beta}_{+,0}$. However, in our case, district compliance with the treatment criterion is imperfect. So, we instead compute the fuzzy RDD estimator for program impact on Y_i as:

$$\hat{\tau}_{FRD}(h) = \frac{\hat{\tau}_{SRD}(h)}{\hat{\varrho}_{SRD}(h)} \tag{10}$$

where $\hat{\varrho}_{SRD}(h)$ is the sharp RDD estimator using observed treatment status D_i for district i as the outcome variable rather than Y_i. In other words, $\hat{\varrho}_{SRD}(h)$ estimates the effect of crossing the cut-off c on the probability of receiving treatment. The estimator $\hat{\tau}_{FRD}(h)$ in (10) is unbiased and consistent under the assumption that crossing the cut-off c only affects

[12] Our methodological approach is similar to that employed in other studies related to the DPEP, such as Khanna (2023) and Sunder (2020). These papers estimate program impacts on a different set of outcomes.

Figure 1: District Treatment Probability



Notes: The graph shows the probability that a district was chosen to receive the DPEP by the district running variable score, which is the difference between the district's female literacy rate and the national average female literacy rate of 39.3 percent in the 1991 Census of India. The graph is constructed using the *rdplot* command in Stata (Calonico et al., 2014).

Y_i via its impact on treatment probability, and that this impact on treatment probability is monotonic. Under these conditions, $\hat{\tau}_{FRD}(h)$ estimates the LATE of the DPEP on Y_i for complying districts.

We aggregate our election outcomes from the constituency level to the district level to perform the estimation at the level of treatment. In Table A.1, we perform a McCrary test for manipulation around the cut-off by testing for any discontinuity in the frequency of district-level observations at the DPEP eligibility cut-off using the non-parametric RDD methodology described above, but assuming a sharp discontinuity and perfect assignment to treatment. We find no evidence of elections being held disproportionately more or less often in eligible or ineligible districts near the cut-off. We conduct estimations on elections in post-program years, i.e., years after the DPEP begins in a district, leveraging the fact that we have treated and control districts in every state that goes to election in any year. We include a full set of state fixed effects, year fixed effects, and state by year fixed effects to respectively control for time-invariant state-level unobservables, aggregate election year shocks common to all states, and state-specific election year shocks that may otherwise be correlated with DPEP treatment status and hence may bias our results. We cluster all standard errors at the level of the running variable, i.e., by district female literacy points. We present adjusted p-values to account for multiple hypotheses testing using the procedure in Anderson (2008).

Our main sample includes elections that took place in the post-program years. We exclude constituencies that are reserved for SC/ST candidates from our estimation sample, so as to capture program impacts in seats with fully open competition (see Section 2.3 for details). We also exclude by-elections from our sample, as these are rare elections held earlier than usual in constituencies facing extraordinary circumstances, such as the death of a sitting MLA. We also conduct falsification tests that estimate "placebo" effects of the DPEP using the same empirical specification but with data from pre-program years. Any differences in our outcomes between treated and untreated districts in placebo regressions would indicate the presence of pre-existing differences in these outcomes that we may erroneously interpret as program impacts in our main specifications. As we show later, all estimated placebo effects are close to zero and statistically insignificant, indicating that our results are in fact capturing the impacts of the DPEP.

6 Main Results

6.1 Predictions 1 and 2: Effects on Types of Candidates and Winners

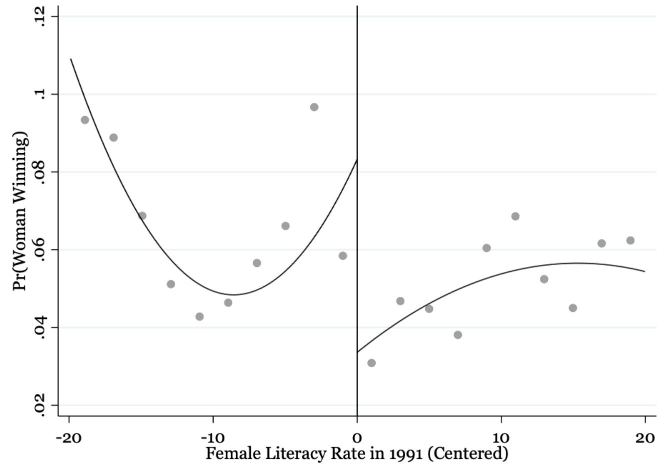
Our model predicts that the DPEP should increase the probability of female candidates winning MLA elections (Prediction 1). Moreover, we expect the program to increase the fraction of female contestants through dropout of low-competence male candidates and potentially also through an increase in the number of female candidates (Prediction 2).

This is exactly what we find in Figure 2 and Table 2.[13] In Panel A of Table 2, we present our estimates of the DPEP's impact on the probability that a female candidate wins an MLA election, on the numbers of women and men contesting for a particular seat, and on the number of candidates contesting that are independent candidates (i.e., not aligned with any political party) and those that are representing an official political party. We report robust standard errors clustered by the running variable in parentheses and Anderson (2008) q-values in brackets. In Panel B, the first-stage estimates across all columns show that for the optimal bandwidths, which lie in the range of 12-14 p.p. on either side of the eligibility threshold, the probability that a district is treated by the DPEP increases by a statistically significant 19.5-21.7 p.p. if the district's female literacy rate in 1991 is below the threshold, verifying that the program eligibility criterion has sufficient explanatory power.

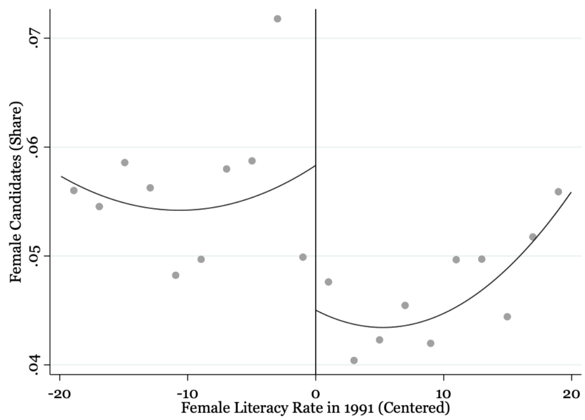
As predicted by our model, we find that women are 22.2 p.p. more likely to win an election in treated districts than in control districts (column (1)). This effect is significant and

[13]Figure 2 contains RDD plots for our primary outcomes: women's probability of winning and the share of female candidates contesting in MLA elections. RDD plots for additional outcomes are available upon request.

Figure 2: Predictions 1 and 2: RDD Graphs for Main Outcomes



(A) Probability of a Woman Being Elected



(B) Share of Female Candidates

NOTE: The figure shows the probability that a woman wins an MLA election (Panel A) and the share of female candidates in MLA elections (Panel B) by the district running variable score, which is the difference between the district's female literacy rate and the national average female literacy rate of 39.3 percent in the 1991 Census of India. The graphs are constructed using the *rdplot* command in Stata (Calonico et al., 2014).

translates into a four-fold increase in the probability that a female wins the election relative to the probability in non-DPEP districts (5.2 percent). When we examine the DPEP's effects on the entry of male and female politicians into the electoral contest, we find that the program increased the fraction of candidates that are female. As columns (2) and (3) show, in an average election in non-DPEP districts, only 5 percent of the contestants are female. The average number of women contesting elections (0.5 women per constituency) is far lower than the average number of male candidates (10 men per constituency). While the effect is not statistically significant (potentially due to the sizable barriers that prevent

Table 2: Predictions 1 and 2: Effects on Types of Candidates and Winners

Panel A	**Female winner**	**# Female candidates**	**# Male candidates**	**# Independent candidates**	**# Party-affiliated candidates**
	(1)	(2)	(3)	(4)	(5)
Treat	0.222	0.046	-5.099	-3.988	-1.002
	(0.091)**	(0.208)	(2.230)**	(1.909)**	(0.780)
	[0.059]*	[0.332]	[0.059]*	[0.059]*	[0.111]
Panel B			**First Stage**		
Cut-off	-0.202**	-0.217**	-0.201**	-0.201**	-0.195**
	(0.084)	(0.081)	(0.085)	(0.085)	(0.086)
Untreated y Mean	0.052	0.466	9.680	5.263	4.897
Observations	1,564	1,816	1,596	1,586	1,532
State FE	x	x	x	x	x
Year FE	x	x	x	x	x
State*Year FE	x	x	x	x	x
Clusters	211	242	215	214	207
Bandwidth	12.339	14.231	12.472	12.424	12.102

Notes: y refers to the dependent variable. Estimates are for unreserved seats only. Robust standard errors clustered by the running variable in parentheses. Anderson (2008) q-values in square brackets. Bandwidth is reported in female literacy rate percentage points around treatment cut-off of 39.3 percent. ***$p < 0.01$; **$p < 0.05$; *$p < 0.10$.

women from entering politics in India, especially at the state level), the DPEP increased the number of female contestants by 10 percent. Additionally, the number of male contestants per constituency experienced a statistically significant 50 percent decline. The results in columns (2)-(3) translate into an increase in the fraction of candidates that are female in treated districts relative to untreated districts.

Column (4) further reveals that the male dropouts in treated districts are overwhelmingly independent candidates, whose numbers decline by 3.99 (76 percent) on average. These independent candidates are the most marginal ones in state elections, with a win rate of only 1.72 percent in over 9,000 elections in unreserved seats in our sample. The number of candidates from official political parties, on the other hand, remains largely unchanged post-program in column (5). These results are consistent with the model's insight of marginal, low-competence male candidates being the ones dropping out from contesting elections as a result of the implementation of the DPEP.

6.2 Prediction 3: Effects on Candidate Competence

Our model predicts that the DPEP should lead to an increase in the competence threshold for male candidates to run for office and reduce the threshold for female candidates. Thus, the average quality of male candidates should improve in DPEP districts relative to non-DPEP districts, while the average competence of women should decline. As the majority of political candidates running for election are male, this should also translate into an increase in average candidate competence in treated districts relative to untreated districts (Prediction 3).

To examine this empirically, in Table 3 we estimate whether the program had an impact on candidate competence using data we collected from candidate affidavits on educational attainment, asset ownership, and criminality. Unfortunately, we do not have a breakdown by gender and so we can only look at average characteristics of the entire pool of candidates. Moreover, this data is only available for 2004-2018, i.e., after the DPEP had ended, as candidate declaration of their attributes was only made a legal requirement in 2004. Hence, this data set is smaller than what we use for our previous results, and our coefficients may be imprecisely estimated. Nevertheless, we find that candidates in DPEP districts are significantly more likely to have secondary education by 15 p.p., which constitutes an 19 percent increase over the already high baseline secondary school attainment rate of 81 percent among candidates in non-DPEP districts. The effect, however, does not remain significant after correcting for multiple hypotheses testing. There is no effect on primary education attainment in column (1), likely due to even higher levels of primary school completion rates among candidates even in the absence of the program (94 percent for candidates in non-DPEP districts). Similarly, we do not find any significant impact on candidates' criminality and asset ownership.

Although our ability to estimate effects on candidate competence is curtailed by data limitations, the increase in candidate educational attainment that we observe is consistent with an increase in the equilibrium competence level among contesting candidates during post-DPEP years.[14] We wish to stress that, because of the timing of the effects, the increase in candidates' schooling is unlikely to be the result of the direct impact of the DPEP on education. In Section 7.4, we will discuss this issue in detail.

6.3 Prediction 4: Heterogeneity by Gender of Past Winner

Recall that our results in Table 2 show no statistically significant increase in the total number of female candidates who contest in post-DPEP elections. In addition to societal barriers that prevent women from entering politics in India, parties may also be unwilling to field female candidates if they (correctly or incorrectly) believe that the prospects of female candidates are not good. However, the DPEP-induced increase in women's probability of winning may have a "demonstration effect" and increase women's candidacy as political parties respond

[14]The program eligibility criteria continue to have strongly significant impact on treatment probability in the first stage estimates of 23.3-27.8 percent across all columns, for optimal bandwidths of 10.50-11.04 literacy points on either side of the cut-off threshold.

Table 3: Prediction 3: Effects on Candidate Competence

Panel A	**Candidate has primary education**	**Candidate has secondary education**	**Candidate has a criminal case**	**Candidate assets**
	(1)	(2)	(3)	(4)
Treat	0.014	0.150	0.038	29.428
	(0.030)	(0.068)**	(0.051)	(18.712)
	[0.478]	[0.108]	[0.437]	[0.211]
Panel B		**First Stage**		
Cut-off	-0.238**	-0.278***	-0.246**	-0.233*
	(0.120)	(0.105)	(0.116)	(0.122)
Untreated y Mean	0.942	0.806	0.150	16.302
Observations	566	705	597	530
State FE	x	x	x	x
Year FE	x	x	x	x
State*Year FE	x	x	x	x
Clusters	218	275	231	206
Bandwidth	11.042	13.911	11.448	10.501

Notes: y refers to the dependent variable. Robust standard errors clustered by the running variable in parentheses. Anderson (2008) q-values in square brackets. Bandwidth is reported in female literacy rate percentage points around treatment cut-off of 39.3 percent. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.10$.

to the increased favorability of women candidates and field them more often (Beaman et al., 2012; Bhalotra et al., 2018; O'Connell, 2018). This insight is consistent with Prediction 4 of our model, which states that the effect of the DPEP on women's likelihood of being elected should be stronger in districts where women were elected in previous elections.

In Table 4, we investigate whether more female candidates contest following a woman's victory in the previous election in treated districts relative to untreated districts.[15] Column (1) shows that the number of female contestants increases significantly by 0.26 candidates in DPEP districts (relative to non-DPEP districts) when the previous election was won by a female, but there is no such effect when a man won the previous election (column (2)).[16] This pattern of results is consistent with parties being more willing to field female candidates as their winning probability increases. Notably, columns (3) and (5) show that this demonstration effect from a female winner is present both for the incumbent party (who

[15]Interestingly, the benefit derived by female candidates, as voters increased the relative weight assigned to leader competence, was accrued irrespective of the gender of the leader who was in power when the DPEP was first implemented in a district. This finding provides support to the "demonstration effect" induced by the DPEP itself. A full set of estimates is reported in Table A.2.

[16]The first stage coefficients are statistically significant, with the eligibility criteria impacting the probability of treatment by 20.0 and 20.1 p.p. for bandwidths of 11.71 and 12.49 literacy points, respectively.

Table 4: Prediction 4: Heterogeneous Effects on Number of Female Candidates by Gender of Past Winner

Panel A	**# Female candidates**		**Incumbent party candidate is female**		**Non-incumbent party candidate is female**	
	(1)	(2)	(3)	(4)	(5)	(6)
	Previous winner is female	Previous winner is male	Previous winner is female	Previous winner is male	Previous winner is female	Previous winner is male
Treat	0.261	-0.217	0.111	-0.045	0.035	0.064
	(0.111)**	(0.236)	(0.049)**	(0.037)	(0.017)**	(0.052)
	[0.075]*	[0.219]	[0.075]*	[0.156]	[0.075]*	[0.069]
Panel B			**First Stage**			
Cut-off	-0.200**	-0.201**	-0.206**	-0.204**	-0.202**	-0.179**
	(0.084)	(0.085)	(0.084)	(0.085)	(0.084)	(0.090)
Untreated y Mean	0.055	0.405	0.021	0.025	0.004	0.038
Observations	1,497	1,605	1,614	1,618	1,596	1,387
State FE	x	x	x	x	x	x
Year FE	x	x	x	x	x	x
State*Year FE	x	x	x	x	x	x
Clusters	202	216	217	218	215	187
Bandwidth	11.705	12.490	12.789	12.831	12.455	10.961

Notes: y refers to the dependent variable. Estimates are for unreserved seats only. Columns (1) and (2) show impact estimates on the number of female candidates contesting a seat for elections where the previous winner was a woman or a man, respectively. Columns (3) and (4) show impact estimates on the probability that the incumbent party that won the seat previously runs a female candidate when the previous winner was a woman or a man, respectively. Columns (5) and (6) show the corresponding estimates for non-incumbent parties that lost previously. Robust standard errors clustered by the running variable in parentheses. Anderson (2008) q-values in square brackets. Bandwidth is reported in female literacy rate percentage points around treatment cut-off of 39.3 percent. ***$p < 0.01$; **$p < 0.05$; *$p < 0.10$.

fielded the winning female candidate in the previous election) as well as for other parties (whose candidates lost to a female candidate in the last election).[17] The probability that the incumbent party and other parties field a female candidate increases, respectively, by five times and nine times in DPEP districts relative to non-DPEP districts if the winner in the previous election was female. Thus, all political parties field more female candidates in DPEP districts after the previous election was won by a woman.[18]

[17]Similar to the results in column (2), there is no effect from a male candidate's win for either incumbent or non-incumbent parties in columns (4) and (6).

[18]In a similar manner, we investigate whether exposure to female leaders at the village level differentially changes the impact of the DPEP on the probability of women winning elections at the state level. We exploit the variation in exposure to village-level female leaders induced by the mandated reservation of one-third of village council seats and headships for women in combination with the differential timing of village council

6.4 Prediction 5: Heterogeneity by Effectiveness of the DPEP

We now turn to the fifth prediction of the model, which states that the effect of the DPEP on women's likelihood of being elected should be stronger in districts where the program was most effectively implemented (i.e., in districts where the DPEP led to greater improvements in the local economy and educational performance).

A. Night Luminosity

In Table 5, we first estimate the impact of the DPEP on district economic growth as measured by district-year nightlight luminosity during post-DPEP years (1994-2013). We estimate this effect separately for districts that had above- versus below-median economic activity prior to the DPEP, proxied by the luminosity in 1994. We select 1994 because it is the first year for which the nightlights data is available and it is also the first year of DPEP implementation making any program effects unlikely. Columns (1) and (2) of Table 5 show the estimated program impacts on total light per square kilometer aggregated to the district level, whereas columns (3) and (4) repeat the analysis for the log of aggregate light per square kilometer in each district. The first stage is only statistically significant for below-median districts (columns (2) and (4)), with the DPEP eligibility criterion impacting the probability of treatment by 39.2 and 41.1 p.p., respectively—likely because the majority of treated districts belong to the below-median luminosity sub-sample. Both columns (2) and (4) show that the DPEP significantly increased economic growth in districts with below-median economic activity prior to the DPEP, with treatment increasing total light by 2.99 and total log light by 1.61, on average. These effects are significant and constitute an increase in district economic activity of 63.3-87.5 percent due to the program. Hence, the DPEP appears to have had a large impact on local economic activity in treated districts that were underperforming at the start of the DPEP.

elections across Indian states. We compare elections results in districts that are exposed to a female leader at the village level for one or more years versus those that have no exposure. We find little evidence that exposure to women's leadership at the local village level leads to differential effects of the DPEP on women winning state parliament elections. These results are available upon request.

Table 5: Prediction 5: Effects on Night Lights and Female Winners

Panel A	**Total Light**		**Log Total Light**		**Woman Wins * AM lights in 1994**	**Woman Wins * BM lights in 1994**
	(1)	(2)	(3)	(4)	(5)	(6)
	If lights AM in 1994	If lights BM in 1994	If lights AM in 1994	If lights BM in 1994		
Treat	3.773	2.985	1.050	1.609	0.055	0.144
	(16.089)	(1.217)**	(2.526)	(0.638)**	(0.064)	(0.073)**
	[0.688]	[0.045]**	[0.686]	[0.045]**	[0.412]	[0.069]*
Panel B			**First Stage**			
Cut-off	0.169	-0.392***	0.195	-0.411***	-0.197**	-0.194**
	(0.187)	(0.137)	(0.185)	(0.137)	(0.092)	(0.097)
Untreated y Mean	4.476	4.703	1.799	1.838	0.037	0.013
Observations	1,280	1,275	1,260	1,275	1,383	1,177
State FE	x	x	x	x	x	x
Year FE	x	x	x	x	x	x
State*Year Trend	x	x	x	x	-	-
State*Year FE	-	-	-	-	x	x
Clusters	114	142	109	140	183	156
Bandwidth	5.754	7.503	5.414	7.310	11.866	10.333

Notes: y refers to the dependent variable. Estimates in columns 5-6 are for unreserved seats only. Nightlights data are for the years 1995-2013. BM and AM denote below median and above median respectively, and pc refers to per cell. Robust standard errors clustered by the running variable in parentheses. Anderson (2008) q-values in square brackets. Bandwidth is reported in female literacy rate percentage points around treatment cut-off of 39.3 percent. ***$p < 0.01$; **$p < 0.05$; *$p < 0.10$.

We then turn to explicitly testing Prediction 5. In columns (5) and (6), we examine whether the increase in women's likelihood of winning occurs in the same districts where the program impact on economic growth is larger. To preserve statistical power, the specification that we use in column (6) is different from the one used in previous columns. Instead of bifurcating the sample into above and below-median districts like we do in columns (1)-(4), in column (5) the outcome variable is constructed by interacting two indicator variables: whether a woman wins in an election times whether the district had above median luminosity (total light per square kilometer) in 1994. Similarly, in column (6), the outcome variable is constructed by interacting: whether a woman wins in an election times whether the district had below median luminosity in 1994. This implies that the outcome variable in column (5) (column (6)) equals one only when the district has a female winner and the district had above (below) median luminosity in 1994, and equals zero otherwise. Consistent with our model, we find the effect of the DPEP on women's likelihood of being elected to be stronger in districts where the program was more successful at improving local economic outcomes. In fact, women's probability of winning increases only in below-median districts (at the start of the DPEP) by a statistically significant 14.4 p.p.

B. Educational Performance

In Table 6, we conduct a similar analysis as in Table 5; instead of night lights, we now investigate heterogeneity by the DPEP's impacts on school infrastructure and student participation at the district level. Using a principal-component analysis and DISE data, we first construct a district-level educational performance index.[19] We then split the districts into two groups (above or below median) based on their pre-DPEP education performance proxied by their 2004-05 educational performance index. Ideally, we would have liked to split the sample based on the index values in a pre-DPEP year, like we do for night lights; however, 2004-05 is the first year for which DISE data is available for all districts in India. Thus, the results in Table 6 should be valid to the extent that the below vs above median ranking of districts was preserved despite improvements in the education performance of treated districts due to the DPEP.

With this caveat in mind, in columns (1) and (2), we estimate the impact of the DPEP on district performance index scores in 2004-05.[20] In column (1) (column (2)), the outcome is

[19]The index is based on the following variables: the share of primary schools built since 1995, the number of pupils appearing for the grade eight final exam, the share of pupils that pass the grade eight final exam, the share of pupils that are enrolled in government primary schools, the share of primary pupils that are girls, the share of pupils enrolled in schools with no constructed building, and the share of primary schools that have only a single teacher.

[20]As the DISE data is a cross-sectional district data set, we include several district-level covariates from the 2001 National Census such as the child sex ratio, decadal population growth, the share of the population from scheduled castes or tribes, and the share of villages with a paved road approach, a primary health

an interaction between whether the district had above (below) median performance index in 2004-05 and the district's performance index score in 2004-05. This implies that the outcome in column (1) (column (2)) equals the district's performance index score in 2004-05 if the district is above (or below) median in 2004-05, but equals zero otherwise. In other words, this approach ensures that the variation in the outcome variable in column (1) (column (2)) is only driven by the variation in the performance of above (or below) median districts in 2004-05. We find that the DPEP only increased the educational performance index in below-median districts in column (2), with treatment increasing the index by 2.74 points; an effect that remains statistically significant at the 10 percent level after correcting for multiple hypotheses testing.

In columns (3) and (4), we investigate whether the DPEP's impact on women's probability of winning elections is larger in districts where the educational performance index is also most improved by the program. Similar to Table 5, the dependent variables in columns (3) and (4) are interactions between an indicator for whether a female wins the election and an indicator for whether the district has above or below median performance index in 2004-05. Consistent with our previous findings and the model predictions, the DPEP increases the probability that women win elections only in districts with below-median educational performance index scores, with treatment increasing this probability by a statistically significant 14.2 p.p. The effect remains significant at the 10 percent level after correcting for multiple hypotheses testing.

7 Additional Results on Mechanisms

The empirical evidence presented above is broadly consistent with the predictions of our model. We have documented an increase in women's candidacy rates and probability of being elected after the implementation of the DPEP in their district. We have argued that these findings are driven by the following mechanism: the effective implementation of the program made leader competence more observable in treated districts, prompting voters to increase the weight that they assign to candidate competence relative to candidate gender and to decrease societal division over attitudes to leader gender. In this section, we present additional evidence that supports this mechanism. We also investigate alternative channels through which the DPEP could have impacted political selection, both inside and outside our model.

centre, and a telephone, telegraph, or post office.

Table 6: Prediction 5: Effects on Education Performance and Female Winners

Panel A	**Edu index in 2004-05 * AM edu in 2004-05**	**Edu index in 2004-05 * BM edu in 2004-05**	**Woman Wins * AM edu in 2004-05**	**Woman Wins * BM edu in 2004-05**
	(1)	(2)	(3)	(4)
Treat	0.796	2.736	0.055	0.142
	(0.568)	(1.352)**	(0.049)	(0.064)**
	[0.121]	[0.095]*	[0.154]	[0.095]*
Panel B		**First Stage**		
Cut-off	-0.274**	-0.264**	-0.213**	-0.231***
	(0.129)	(0.117)	(0.089)	(0.086)
Untreated y Mean	0.430	-0.450	0.023	0.030
Observations	158	215	1,449	1,527
State FE	x	x	x	x
Year FE	x	x	x	x
State*Year FE	-	-	x	x
Clusters	154	208	200	211
Bandwidth	8.519	11.210	11.897	12.447

Notes: y refers to the dependent variable. Estimates in columns (3) and (4) are for unreserved seats only. BM and AM denote below median and above median respectively. Columns (1) and (2) include the following district-level covariates from the 2001 Census: the child sex ratio, decadal population growth, population share of scheduled castes/tribes, and share of villages with safe drinking water, electricity, a paved road approach, a primary health centre, and a telephone/telegraph/post office. Year fixed effects in columns (1) and (2) are for the first year of DPEP implementation in the state. Robust standard errors clustered by the running variable in parentheses. Anderson (2008) q-values in square brackets. Bandwidth is reported in female literacy rate percentage points around treatment cut-off of 39.3 percent. ***$p < 0.01$; **$p < 0.05$; *$p < 0.10$.

7.1 DPEP and Anti-incumbency

We now examine whether the program changed voters' pro- or anti-incumbency behavior with respect to the political party currently ruling their constituency. Table A.3 in the Appendix shows our estimated program impacts on the probability that voters re-elect the incumbent party in their constituency, and the gender composition of winners from incumbent and non-incumbent parties.[21] The baseline re-election rate for incumbent parties in our sample of elections is only 28.5 percent in column (1), highlighting the anti-incumbency sentiment voters historically demonstrate in state elections. However, column (1) also shows a statistically significant increase in the re-election probability of incumbent political parties of 26 p.p. in treated districts. This effect is indicative of a notable increase in voters' pro-incumbency sentiment of nearly 91 percent from the baseline re-election rate, suggesting a decline in voters' desire to punish ruling politicians in DPEP districts. This finding is consistent with the rising equilibrium competence among ruling politicians in treated districts relative to untreated districts.

In columns (2) and (3), we estimate whether the probability of a candidate from the incumbent party winning due to the DPEP affects male and female candidates differently. The coefficient in column (2) shows a positive but insignificant effect of the program on the winning probability of male candidates from the incumbent party, but in column (3) we find a significant 7.5 p.p. increase in the probability that female candidates from incumbent parties win; this is a four-fold increase from the baseline rate of 1.8 percent. Hence, the increase in pro-incumbency effect we find in column (1) appears to be driven at least partially by voters' greater willingness to elect women. In columns (4) and (5), we similarly estimate post-program changes in the probability that male and female non-incumbent party candidates win election. Here, we find a marked shift in the gender composition of winning candidates, with the probability that a male candidate from a non-incumbent party wins declining by a statistically significant 40.7 p.p. from a baseline win rate of 67.8 percent in column (4), and the probability that a female candidate from a non-incumbent party wins increasing by a statistically significant 15.5 p.p. from a baseline win rate of 3.5 percent in column (5). Again, the results show marked gains in the winning probability for female candidates, with larger gains for female candidates from non-incumbent parties in column (5) than for female candidates from the incumbent party in column (2). The sharpest change post-program, however, is the decline in male non-incumbent winners in column (4), which is only partially offset by the increase in female non-incumbent winners. The net program effect is an overall

[21] We find strongly significant first stage impacts of the eligibility criteria across all columns of 18.8-20.4 p.p. for optimal bandwidths of 11.01-12.47 literacy points.

increase in voters' pro-incumbency from historically low levels and a rise in the number of female MLAs elected in treated districts. Both these findings are consistent with increased levels of candidate competence in treated districts, and increased voter prioritisation of this quality over male leadership.

7.2 DPEP and Political Alignment

We next examine whether the DPEP altered voters' propensity to vote for candidates aligned with the party that wins the most seats statewide, and is likely to govern the state on its own or in a coalition. As with our results on incumbency, we also disaggregate the impacts of the DPEP on the probability of male and female candidates winning based on whether they are aligned or unaligned. Table A.4 in the Appendix presents these results.[22] In column (1), we find a large, statistically significant decline in voters' propensity to vote for aligned candidates of 37 p.p. in DPEP districts (a marked reversal from the historically high win rate of 58.2 percent at baseline for aligned candidates). This effect captures a large reduction in voters' desire to align with the ruling government after the program, despite the patronage benefits of alignment, which is consistent with a compensatory increase in candidate competence that voters are willing to choose instead.

Columns (2)-(4) show that the estimated effect on party alignment is driven by a large decline in winning probability of aligned male candidates. Such a decline benefits both male and female non-aligned candidates, with non-aligned males benefiting more than non-aligned females. Interestingly, we do not observe a decrease in the winning probability of aligned females; in fact, the probability that female aligned candidates win election increases by 17.8 p.p. from a baseline win rate of 3.5 percent (once again pointing to a meaningful increase in voters' willingness to elect women due to the DPEP). On the other hand, the probability that male aligned candidates win election declines by 54.7 p.p., completely eliminating the baseline win probability of 54.6 percent for male aligned candidates in the absence of the program. The probability that male unaligned candidates win election in turn increases by 33.2 p.p., which nearly doubles their baseline win probability of 40.4 percent. There is a small concomitant increase of 4.8 p.p. in the probability that female unaligned candidates win as well. This aggregate shift in voter preferences away from alignment with government towards unaligned candidates is supportive of our hypothesis that voters increasingly prioritize leader competence following the DPEP, and are consequently more willing to sacrifice state patronage.

[22] Across all columns, program eligibility has a strongly significant positive impact of 19.9-21.0 p.p. on the probability of treatment in the first stage, for optimal bandwidths of 11.79-13.20 literacy rate points.

7.3 Effect on Gender Bias among Voters

The relative weight that voters assign to leader competence compared to leader gender can increase not just through an increase in the weight that voters assign to competence, but also via a decrease in voters' gender bias. This could occur if exposure to the DPEP made the average voter less male-biased due to improvements in their educational attainment.[23] Although in Section 7.4 we rule out that our results are driven by the increase in educational attainment of residents in DPEP districts, in this section, we indirectly examine the extent to which the DPEP led to a decline in voters' gender bias against female politicians. To do so, we investigate the differential effect of the DPEP on women's win probability in "decisive" versus "indecisive" state elections.

We first define a *constituency* as having been won decisively if the victory vote margin lies in the highest quartile in the historical distribution of victory margins in all past elections in that constituency. We then define a *state* election to be a decisive state election if the share of constituencies across the state being won with decisive margins in that election is above the historical median in the distribution of all past elections for that state. Defined in this manner, our "decisive state election" variable seeks to capture the strength of voters' preference for a certain party in a state. In decisive state elections, candidate gender is less likely to matter to voters than their party affiliation even in the absence of the DPEP. In such states, even a relatively small decline in voters' gender bias due to the DPEP may be sufficient to increase the probability of a female win. On the other hand, in indecisive state elections, a larger decline in voters' gender bias is needed to observe an increase in the likelihood of a female candidate winning the election.

In Table A.5, columns (1) and (2) present estimates of program impact on women's likelihood of winning in indecisive and decisive state elections, respectively. The results reveal that the increase in women's probability of winning elections due to the DPEP that we have documented thus far occurs *exclusively* in decisive elections. The coefficient estimate in column (1), although positive, is insignificant, whereas column (2) shows a statistically significant increase of 14.8 p.p. in the probability that women win in a decisive election environment. To the extent that states with decisive and indecisive elections do not differ in terms of the demonstrated positive impact of the DPEP, the heterogeneous effects in columns (1)-(2) capture the influence of DPEP-induced decline in voters' gender bias on election outcomes.

[23] Alternatively, the DPEP may have increased female voter turnout relative to male voter turnout, which would, under the (reasonable) assumption that female voters tend to be less biased against female leaders, lower the average male-bias among voters. Unfortunately, the SHRUG data does not provide turnout by gender, preventing us from examining this channel directly.

The fact that voters' willingness to elect women manifests more acutely in treated districts (relative to untreated districts) only in decisive state elections indicates that the DPEP-induced reduction in voters' gender bias was not large enough to change the election outcomes in favor of women in all state elections. Columns (3) and (4) show that this result holds irrespective of whether the female candidate running in an indecisive state election is aligned or unaligned. Moreover, female candidates in treated districts in decisive state elections benefit from reduced voter gender bias *only* when they are aligned with the party that wins the most seats statewide, and are thus in a position to provide voters with patronage benefits as a member of state government. Aligned female candidates in DPEP districts experience an increase in their win probability of 11.6 p.p. in column (5) from a baseline win rate of 2.5 percent in non-DPEP districts. No such increase in win probability is observed for unaligned female candidates in decisive state elections in column (6).[24]

In sum, although effective implementation of the DPEP reduced voters' gender bias, it significantly increased women's ability to win elections only for aligned female candidates in decisive state elections that are "safer" for voters in terms of their ability to derive patronage benefits from the state government. In situations where the voters are less certain about which party will win, exposure to the DPEP is insufficient to increase women's ability to win elections.

7.4 Alternative Mechanism

An alternative mechanism for the DPEP's impact on the gender composition and quality of winners is the increase in educational attainment of residents in DPEP districts. First, the DPEP could have increased the educational attainment of an average candidate because of direct exposure to the DPEP (Martinez-Bravo, 2017). Second, the DPEP could have also increased the educational attainment of voters, as suggested by prior literature on the program, and more educated voters may assign a higher weight to candidate quality relative to candidate gender, or may be better able to assess candidate quality, than less educated voters (Banerjee et al., 2011; Marshall, 2016). While both of these effects are likely to occur in the long-run as individuals directly affected by the DPEP during their primary-schooling become old enough to vote and run for office, the timing of our results suggest that this is unlikely to be the main mechanism for our findings.

In Table A.6, we examine whether the effect of the DPEP on the likelihood of female candidates winning state elections varies by the number of years since DPEP implementation in the district. In column (1), we examine election outcomes within the first seven years after

[24]We confirm in Appendix Table A.7 that these findings continue to hold if we use alternate percentile cut-offs to define a decisive victory margin.

the DPEP begins in a treated district, and in column (2) we focus on elections that occurred eight years or more after the DPEP began. If the program effect is only due to increased primary education in the directly treated population, which may in turn have influenced their voting behavior or the average education or quality of candidates, we should observe no effect in column (1). This is because directly treated primary-age cohorts would nearly all be below the minimum age for voting (18 years) and for contesting MLA elections (25 years) during the first seven years of program implementation. The increase in women's win probability that we find in Table 2 should then only appear in column (2) of Table A.6. On the other hand, if the impact of the DPEP occurs via our hypothesized mechanism of demonstrated leader competence, that adults old enough to vote then prioritize more than leader gender, we should also observe an effect in column (1), which may persist in column (2) as well if the impact is long-lasting. Indeed, column (1) shows a large, statistically significant 39.5 p.p. positive impact of the DPEP on women's likelihood of winning within the first seven years of the program. Column (2) shows that the effect persists in subsequent years, with female candidates continuing to be 21.5 p.p. more likely to win in treated relative to non-treated districts. In columns (3) and (4), we perform the same exercise, but for elections within the first nine years of treatment and those ten years or more after treatment, respectively, to check whether the results are robust to alternative definitions for "young" and "old" cohorts. The same pattern of results emerges in columns (3) and (4), with women in treated districts being 33.6 p.p. and 27 p.p. more likely to win while the DPEP was being implemented as well as after the DPEP was over.

The findings above are strongly supportive of our hypothesis that demonstrated leader competence is the mechanism behind our results, as the impact of the DPEP on women's likelihood of winning MLA elections occurs early in its implementation when the electorate is comprised of voters who are not direct beneficiaries of the increase in primary education. Further, the DPEP's impact is long-lasting, and persists even after the program implementation has stopped, indicating a long-term change in voters' preferences.

8 Robustness Checks

To ensure that our findings are not driven by pre-existing differences between treated and untreated districts, we restrict the sample to election years prior to the introduction of the DPEP and estimate placebo "treatment" effects using our fuzzy RDD methodology. Table A.8 presents the results from these placebo regressions for the same outcomes as in Table 2. For all outcomes, we find no statistically significant differences between treated and untreated districts in elections held during years prior to the introduction of the DPEP. We perform the same exercise in Tables A.9, A.10, and A.11 to test for pre-existing differences between treated and untreated districts in outcomes analyzed in Tables A.3, A.4, and A.5, respectively, and find no significant effects.[25]

9 Discussion

Before concluding the paper, we make the following observations about the magnitudes and interpretation of our estimates. First, our estimated impacts of the DPEP on women's political participation are sizable vis-à-vis other programs. Prillaman (2023), for instance, evaluates a program aimed at expanding women's social networks and access to credit groups in India, finding that it led to a 100 percent increase in political activity for women in treated villages compared to control villages. The impact of the DPEP on the likelihood of women being elected as state MLAs is estimated to be four times larger. Our analysis also indicates that, in districts where a woman won the previous election, the DPEP induced an increase in the number of female candidates for state legislature that is almost twice as large as the effect of ten years of exposure to quota-induced female leadership at the local level (O'Connell, 2018). Finally, Bhalotra et al. (2018) show that the event of a woman winning an election leads to a sizable 18.5 p.p. increase in the probability of a major party fielding at least one female candidate in the subsequent election. Our estimates of the "demonstration effect" of the DPEP discussed in Table 4 are similar in magnitude.

Second, in light of various studies documenting the favorable impact of female political leadership, we argue that the effective implementation of public programs like the DPEP may have far-reaching and broad consequences. For example, Chattopadhyay and Duflo (2004) exploit gender quotas in India's local elections to show that female local leaders are more likely to invest in public goods, such as drinking water, roads, informal and formal education, and irrigation. Iyer et al. (2012) document an increase in reported crimes against women, rapes, and kidnapping of women when a woman is elected in local elections (this is good news since it reflects improvements in reporting rather than a rise in actual crimes). Beaman et al. (2012) also find that female leadership can influence adolescent girls' career aspirations and educational attainment. Specifically, they show that the gender gap in aspirations closed by 20 percent in parents and 32 percent in adolescents in villages assigned a female leader for two election cycles. While these studies focus on women's political representation at the village level, impacts at higher levels (such as state or national levels) are possible (O'Connell,

[25] One may be concerned that the DPEP eligibility criterion does not lead to a statistically significant increase in treatment probability in the first stage in some of these placebo regressions, so we re-estimate the placebo regressions using a parametric two-stage least squares procedure. This approach introduces the risk of specification error bias, but requires less power than our preferred non-parametric procedure. In Table A.12, we find that the DPEP eligibility criterion has a statistically significant impact on the probability of treatment in the first stage for nearly all outcomes. Reassuringly though the second-stage coefficients are still insignificant in this table.

2018). With an estimated four-fold increase in the probability of women being elected to state legislatures following the DPEP, we could expect the positive effects of the program to go far beyond its stated goals.

Third, while the SHRUG data on candidates and winners allows us to rigorously and effectively study the impact of the DPEP on women's political participation, our data on candidate characteristics is arguably less suitable to test the third prediction of our model: it is only available for post-DPEP years; it also contains a limited set of candidate traits, which only vaguely proxy their quality. It is essential to take this into account when interpreting our estimates of the effects (or lack thereof) of the DPEP on candidate competence (Table 3). Relatedly, detailed data on voter preferences and priorities is lacking. Consequently, when testing the mechanisms behind our main findings, we can only rely on indirect evidence of the impact of the DPEP on the importance of leader competence relative to their gender.

10 Conclusions

Gender inequality in India is a complex and multifaceted phenomenon. The existence of a sizable gender gap in political participation and leadership is a clear illustration of such inequality. Importantly, women's underrepresentation in political office inevitably contributes to the persistence of gender inequality in many other spheres of society.

We show that effective policy implementation can alter political selection by inducing voters to re-weight their priorities in favor of leader competence relative to other leader traits. Specifically, we examine the trade-off made by voters between candidate quality and candidate gender in the context of state elections in India. Exploiting exogenous variation in the implementation of a nationwide schooling expansion program, we show that women are more likely to be elected in treated districts relative to untreated districts even after the program has ended. This improvement in women's political representation takes place through a large decline in the number of male contestants, a smaller increase in the number of female candidates, and, in some circumstances, a decline in voters' gender bias against female candidates. Our findings are broadly consistent with the predictions of a probabilistic voting model where voters trade off candidate competence with their bias against electing female leaders, and male and female candidates have to decide whether to run for office.

Future work should examine whether the DPEP-induced improvements in women's political representation in state legislatures subsequently led to more favorable outcomes for female constituents, better development outcomes, reduced corruption, and perhaps greater representation of women in the national parliament through pipeline effects. Additionally, more work is needed to understand the conditions under which elected leaders can more effectively demonstrate their competence to voters. This is a crucial channel through which political selection can become more driven by competence rather than ideology or gender.

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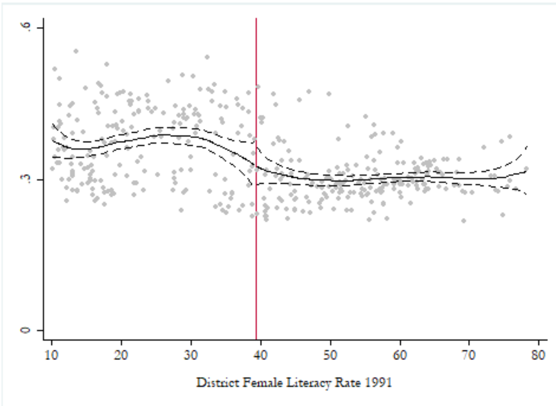
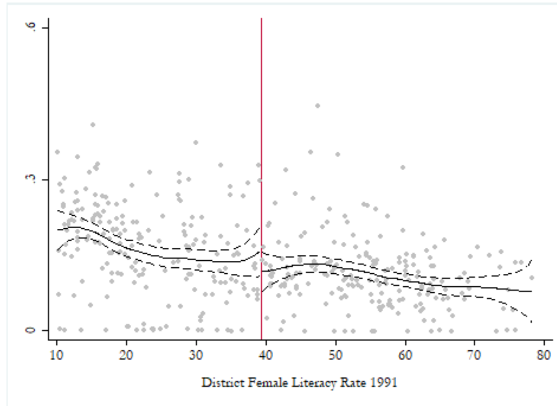
A Online Appendix

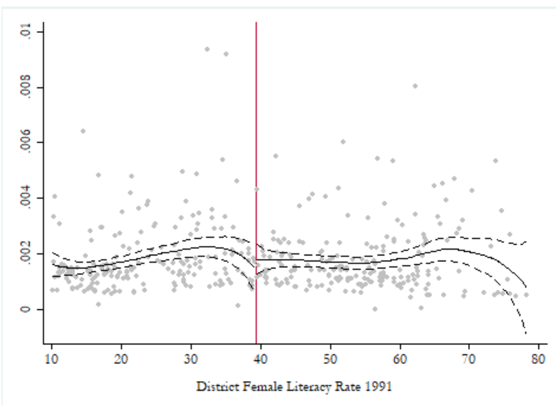
Figure A.1: 1991 Census District Characteristics



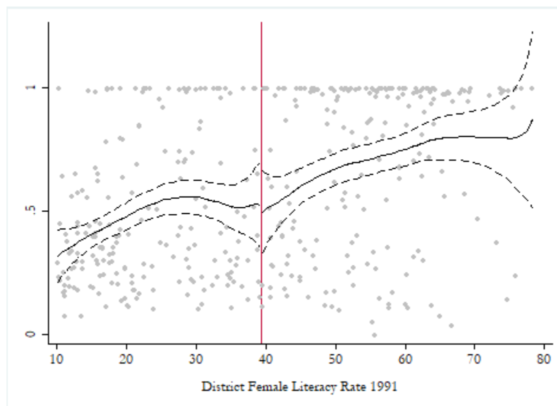
(a) Employment Rate



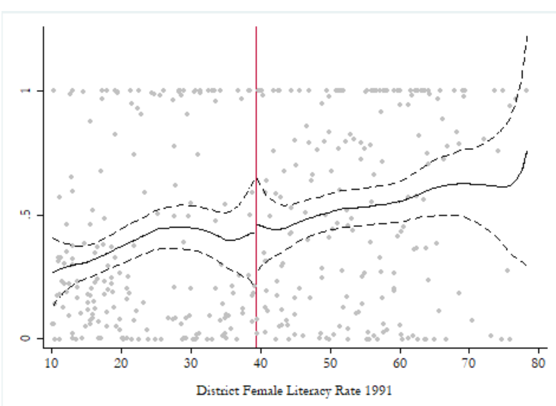
(b) SC Population Ratio



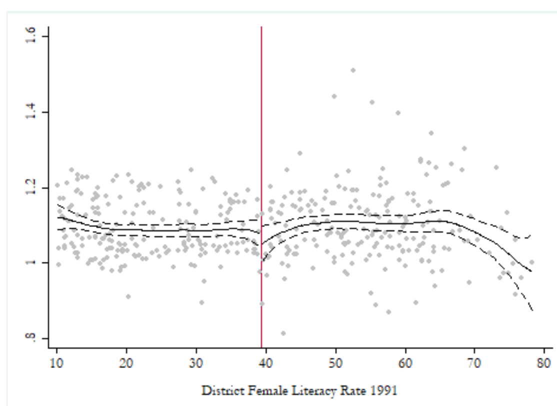
(c) Villages: Per Capita Primary Schools



(d) Villages: Paved Approach



(e) Villages: Power All-Use



(f) Male-Female Sex Ratio

Notes: The graphs show smoothed averages of district characteristics in the 1991 Census of India by the district female literacy rate in the 1991 Census of India, and local linear regression plots with a triangular kernel on either side of the female literacy rate cut-off of 39.3 percent.

Table A.1: McCrary Test

	No. of districts		
	h	$2h$	$0.5h$
	(1)	(2)	(3)
Treat	-1.213	-1.207	-0.241
	(1.215)	(1.223)	(1.499)
y Mean	10.157	10.432	10.224
Observations	139	266	80
Clusters	139	266	80
Bandwidth	7.389	14.778	3.694

Notes: y refers to the dependent variable. h refers to the optimal bandwidth calculated using the algorithm in Calonico et al. (2019). Robust standard errors clustered by running variable in parentheses. Bandwidth is reported in female literacy rate percentage points around treatment cut-off of 39.3 percent. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.10$.

Table A.2: Leader Identity at Implementation and Female Winners

Panel A	**Female winner**			
	(1)	(2)	(3)	(4)
	If leader at implementation was:			
	Female	***Male***	***From same party***	***From different party***
Treat	0.039	0.115	0.043	0.177
	(0.016)**	(0.046)**	(0.016)***	(0.085)**
	[0.020]**	[0.020]**	[0.020]**	[0.020]**
Panel B	**First Stage**			
Cut-off	-0.203**	-0.174*	-0.185**	-0.203**
	(0.093)	(0.093)	(0.089)	(0.084)
Untreated y Mean	0.000	0.000	0.000	0.052
Observations	1,000	1,169	1,507	1,586
State FE	x	x	x	x
Year FE	x	x	x	x
State*Year FE	x	x	x	x
Clusters	135	158	203	214
Bandwidth	8.038	9.525	11.834	12.449

Notes: y refers to the dependent variable. Estimates are for unreserved seats only. Robust standard errors clustered by the running variable in parentheses. Anderson (2008) q-values in square brackets. Bandwidth is reported in female literacy rate percentage points around treatment cut-off of 39.3 percent. ***$p < 0.01$; **$p < 0.05$; *$p < 0.10$.

Table A.3: Effects on Incumbency

Panel A	**Winner is:**				
	Incumbent	**Male from incumbent party**	**Female from incumbent party**	**Male from non-incumbent party**	**Female from non-incumbent party**
	(1)	(2)	(3)	(4)	(5)
Treat	0.260	0.187	0.074	-0.407	0.155
	(0.156)*	(0.141)	(0.040)*	(0.193)**	(0.067)**
	[0.096]*	[0.114]	[0.096]*	[0.096]*	[0.096]*
Panel B	**First Stage**				
Cut-off	-0.197**	-0.199**	-0.188**	-0.201**	-0.204**
	(0.086)	(0.085)	(0.087)	(0.085)	(0.084)
Untreated y Mean	0.285	0.269	0.018	0.678	0.035
Observations	1,532	1,555	1,387	1,586	1,596
State FE	x	x	x	x	x
Year FE	x	x	x	x	x
State*Year FE	x	x	x	x	x
Clusters	207	210	187	214	215
Bandwidth	12.156	12.290	11.009	12.444	12.471

Notes: y refers to the dependent variable. Estimates are for unreserved seats only. "Incumbent" refers to the party the currently elected candidate belongs to. Robust standard errors clustered by the running variable in parentheses. Anderson (2008) q-values in square brackets. Bandwidth is reported in female literacy rate percentage points around treatment cut-off of 39.3 percent. ***$p < 0.01$; **$p < 0.05$; *$p < 0.10$.

Table A.4: Effects on Alignment with Ruling Party

	Winner is:				
Panel A	**Aligned**	**Aligned male**	**Aligned female**	**Non-aligned male**	**Non-aligned female**
	(1)	(2)	(3)	(4)	(5)
Treat	-0.370	-0.547	0.178	0.332	0.048
	(0.169)**	(0.191)***	(0.071)**	(0.164)**	(0.032)
	[0.032]**	[0.022]**	[0.025]**	[0.034]**	[0.058]*
Panel B	**First Stage**				
Cut-off	-0.210**	-0.210**	-0.204**	-0.208**	-0.199**
	(0.083)	(0.083)	(0.085)	(0.083)	(0.085)
Untreated y Mean	0.582	0.546	0.035	0.404	0.016
Observations	1,532	1,555	1,387	1,586	1,596
State FE	x	x	x	x	x
Year FE	x	x	x	x	x
State*Year FE	x	x	x	x	x
Clusters	225	224	217	221	203
Bandwidth	13.200	13.156	12.780	12.941	11.794

Notes: y refers to the dependent variable. Estimates are for unreserved seats only. “Aligned” implies that the winning candidate is aligned with the party that wins the largest number of seats in the state. Robust standard errors clustered by the running variable in parentheses. Anderson (2008) q-values in square brackets. Bandwidth is reported in female literacy rate percentage points around treatment cut-off of 39.3 percent. ***$p < 0.01$; **$p < 0.05$; *$p < 0.10$.

Table A.5: Decisive Elections and Female Winners

	Winner is female					
Panel A	**If indecisive**	**If decisive**	**If indecisive**		**If decisive**	
	(1)	(2)	(3)	(4)	(5)	(6)
			If aligned	if not aligned	If aligned	If not aligned
Treat	0.070	0.148	0.056	0.015	0.116	0.032
	(0.047)	(0.064)**	(0.037)	(0.021)	(0.053)**	(0.024)
	[0.164]	[0.095]*	[0.164]	[0.267]	[0.095]*	[0.166]
Panel B	**First Stage**					
Cut-off	-0.196**	-0.197**	-0.196**	-0.196**	-0.195**	-0.191**
	(0.086)	(0.084)	(0.086)	(0.086)	(0.085)	(0.086)
Untreated y Mean	0.021	0.032	0.011	0.009	0.025	0.007
Observations	1,605	1,497	1,614	1,532	1,479	1,434
State FE	x	x	x	x	x	x
Year FE	x	x	x	x	x	x
State*Year FE	x	x	x	x	x	x
Clusters	216	202	217	207	198	192
Bandwidth	12.611	11.721	12.631	12.099	11.408	11.150

Notes: y refers to the dependent variable. Estimates are for unreserved seats only. We define a state election to be a "decisive" ("indecisive") state election if the share of constituencies across the state being won with decisive margins in that election is above (below) the historical median in the distribution of all past elections for that state. We define a constituency as having been won decisively if the victory vote margin lies in the highest quartile in the historical distribution of victory margins in all past elections in that constituency. "Aligned" implies that the winning candidate is aligned with the party that wins the largest number of seats in the state. Robust standard errors clustered by the running variable in parentheses. Anderson (2008) q-values in square brackets. Bandwidth is reported in female literacy rate percentage points around treatment cut-off of 39.3 percent. ***$p < 0.01$; **$p < 0.05$; *$p < 0.10$.

Table A.6: Timing of Impact

Panel A	**Female winner**			
Years since start of DPEP:	$< 8\,years$	$\geq 8\,years$	$< 10\,years$	$\geq 10\,years$
	(1)	(2)	(3)	(4)
Treat	0.395	0.215	0.336	0.270
	(0.185)**	(0.097)**	(0.149)**	(0.124)**
	[0.034]**	[0.034]**	[0.034]**	[0.034]**
Panel B	**First Stage**			
Cut-off	-0.153	-0.149	-0.162	-0.076
-0.079	-0.088			
	(0.141)	(0.140)	(0.141)	(0.125)
(0.118)	(0.127)			
Untreated y Mean	0.053	0.052	0.052	0.052
Observations	1,147	1,740	1,377	1,348
State FE	x	x	x	x
Year FE	x	x	x	x
State*Year FE	x	x	x	x
Clusters	187	258	219	208
Bandwidth	11.025	15.282	12.902	12.209

Notes: y refers to the dependent variable. Estimates are for unreserved seats only. Robust standard errors clustered by the running variable in parentheses. Anderson (2008) q-values in square brackets. Bandwidth is reported in female literacy rate percentage points around treatment cut-off of 39.3 percent. ***$p < 0.01$; **$p < 0.05$; *$p < 0.10$.

Table A.7: Alternate Definitions of a Decisive Election

	Woman Winner					
Panel A	**p70**		**p60**		**p50**	
	Indecisive	Decisive	Indecisive	Decisive	Indecisive	Decisive
	(1)	(2)	(3)	(4)	(5)	(6)
Treat	0.068	0.149	0.051	0.165	0.075	0.141
	(0.048)	(0.062)**	(0.045)	(0.064)***	(0.049)	(0.057)**
	[0.106]	[0.035]**	[0.146]	[0.035]**	[0.102]	[0.035]**
Panel B	**First Stage**					
Cut-off	-0.193**	-0.201**	-0.192**	-0.202**	-0.197**	-0.199**
	(0.087)	(0.084)	(0.087)	(0.084)	(0.086)	(0.085)
Untreated y Mean	0.022	0.030	0.021	0.030	0.022	0.031
Observations	1,569	1,507	1,564	1,532	1,605	1,507
State FE	x	x	x	x	x	x
Year FE	x	x	x	x	x	x
State*Year FE	x	x	x	x	x	x
Clusters	212	203	211	207	216	203
Bandwidth	12.386	11.985	12.347	12.104	12.585	11.815

Notes: y refers to the dependent variable. Estimates are for unreserved seats only. p70, p60, and p50 refer to the definition of a decisive winning margin in a constituency, set at the 70th percentile, 60th percentile, and 50th percentile of the historical distribution of winning margins in all past elections in that constituency respectively. In all columns, the definition of statewide winning margins being "indecisive" or "decisive" are if the share of seats with decisive winning margins are below or above the historical median in the distribution of all past state elections respectively. Robust standard errors clustered by the running variable in parentheses. Anderson (2008) q-values in square brackets. Bandwidth is reported in female literacy rate percentage points around treatment cut-off of 39.3 percent. ***$p < 0.01$; **$p < 0.05$; *$p < 0.10$.

Table A.8: Placebo tests: Effects on types of candidates and winners

Panel A	**Female winner**	**# Female candidates**	**# Male candidates**	**# Independent candidates**	**# Party-affiliated candidates**
	(1)	(2)	(3)	(4)	(5)
Treat	0.113	-0.312	-1.964	-2.428	-0.369
	(0.107)	(0.415)	(3.592)	(3.228)	(0.930)
	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]
Panel B			**First Stage**		
Cut-off	-0.157*	-0.127	-0.126	-0.124	-0.140
	(0.090)	(0.103)	(0.103)	(0.100)	(0.093)
Untreated y Mean	0.052	0.459	9.820	5.351	4.910
Observations	1,550	1,165	1,145	1,265	1,475
State FE	x	x	x	x	x
Year FE	x	x	x	x	x
State*Year FE	x	x	x	x	x
Clusters	199	149	146	162	189
Bandwidth	11.774	9.422	9.260	9.941	11.198

Notes: y refers to the dependent variable. Estimates are for unreserved seats only. Robust standard errors clustered by running variable in parentheses. Anderson (2008) q-values in square brackets. Bandwidth is reported in female literacy rate percentage points around treatment cut-off of 39.3 percent. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.10$.

Table A.9: Placebo tests: Effects on incumbency

	Winner is:				
Panel A	**Incumbent**	**Male from incumbent party**	**Female from incumbent party**	**Male from non-incumbent party**	**Female from non-incumbent party**
	(1)	(2)	(3)	(4)	(5)
Treat	0.155	0.056	0.080	-0.152	0.051
	(0.188)	(0.165)	(0.057)	(0.232)	(0.087)
	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]
Panel B	**First Stage**				
Cut-off	-0.129	-0.134	-0.128	-0.126	-0.167*
	(0.097)	(0.095)	(0.098)	(0.101)	(0.088)
Untreated y Mean	0.290	0.269	0.018	0.674	0.035
Observations	1,532	1,555	1,387	1,586	1,596
State FE	x	x	x	x	x
Year FE	x	x	x	x	x
State*Year FE	x	x	x	x	x
Clusters	173	182	170	158	211
Bandwidth	10.544	10.862	10.445	9.636	12.455

Notes: y refers to the dependent variable. Estimates are for unreserved seats only. "Incumbent" refers to the party the currently elected candidate belongs to. Robust standard errors clustered by the running variable in parentheses. Anderson (2008) q-values in square brackets. Bandwidth is reported in female literacy rate percentage points around treatment cut-off of 39.3 percent. ***$p < 0.01$; **$p < 0.05$; *$p < 0.10$.

Table A.10: Placebo tests: Effects on alignment with ruling party

	Winner is:				
Panel A	**Aligned**	**Aligned male**	**Aligned female**	**Non-aligned male**	**Non-aligned female**
	(1)	(2)	(3)	(4)	(5)
Treat	-0.581	-0.646	0.109	0.618	-0.010
	(0.364)	(0.379)*	(0.081)	(0.398)	(0.058)
	[0.253]	[0.253]	[0.253]	[0.253]	[0.288]
Panel B	**First Stage**				
Cut-off	-0.128	-0.130	-0.163*	-0.126	-0.130
	(0.098)	(0.096)	(0.089)	(0.099)	(0.097)
Untreated y Mean	0.598	0.559	0.036	0.385	0.015
Observations	1,324	1,359	1,613	1,285	1,404
State FE	x	x	x	x	x
Year FE	x	x	x	x	x
State*Year FE	x	x	x	x	x
Clusters	170	175	207	164	181
Bandwidth	10.414	10.686	12.326	10.132	10.859

Notes: y refers to the dependent variable. Estimates are for unreserved seats only. "Aligned" implies that the winning candidate is aligned with the party that wins the largest number of seats in the state. Robust standard errors clustered by the running variable in parentheses. Anderson (2008) q-values in square brackets. Bandwidth is reported in female literacy rate percentage points around treatment cut-off of 39.3 percent. ***$p < 0.01$; **$p < 0.05$; *$p < 0.10$.

Table A.11: Placebo tests: Decisive elections and female winners

	Winner is female					
Panel A	**If indecisive**	**If decisive**	**If indecisive**		**If decisive**	
	(1)	(2)	(3)	(4)	(5)	(6)
			If aligned	if not aligned	If aligned	If not aligned
Treat	0.045	0.084	0.031	0.015	0.081	-0.010
	(0.049)	(0.086)	(0.039)	(0.021)	(0.063)	(0.048)
	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]
Panel B	**First Stage**					
cut-off	-0.150	-0.166*	-0.139	-0.162*	-0.170*	-0.139
	(0.092)	(0.090)	(0.094)	(0.089)	(0.088)	(0.094)
Untreated y Mean	0.020	0.032	0.011	0.009	0.025	0.007
Observations	1,550	1,711	1,497	1,589	1,700	1,535
State FE	x	x	x	x	x	x
Year FE	x	x	x	x	x	x
State*Year FE	x	x	x	x	x	x
Clusters	199	218	192	204	217	197
Bandwidth	11.945	13.043	11.352	12.235	13.003	11.667

Notes: y refers to the dependent variable. Estimates are for unreserved seats only. We define a state election to be a "decisive" ("indecisive") state election if the share of constituencies across the state being won with decisive margins in that election is above (below) the historical median in the distribution of all past elections for that state. We define a constituency as having been won decisively if the victory vote margin lies in the highest quartile in the historical distribution of victory margins in all past elections in that constituency. "Aligned" implies that the winning candidate is aligned with the party that wins the largest number of seats in the state. Robust standard errors clustered by the running variable in parentheses. Anderson (2008) q-values in square brackets. Bandwidth is reported in female literacy rate percentage points around treatment cut-off of 39.3 percent. ***$p < 0.01$; **$p < 0.05$; *$p < 0.10$.

Table A.12: Election Outcomes, Parametric Placebo

	(1)	(2)	(3)	(4)	(5)
Panel A	**Female winner**	**# Male Candidates**	**Winner is incumbent**	**Winner is aligned female**	**Winner is female if decisive**
Treat	0.129	-2.116	0.067	0.086	0.044
	(0.090)	(3.502)	(0.132)	(0.055)	(0.069)
	[0.610]	[0.610]	[0.610]	[0.610]	[0.610]
Panel B			**First Stage**		
Cut-off	0.238***	0.149	0.211**	0.264***	0.211**
	(0.087)	(0.099)	(0.090)	(0.089)	(0.090)
Untreated y Mean	0.053	9.787	0.289	0.035	0.030
Observations	1,460	1,111	1,350	1,487	1,359
State FE	x	x	x	x	x
Year FE	x	x	x	x	x
Clusters	187	141	174	190	175
Bandwidth	11.143	8.835	10.619	11.233	10.653

Notes: y refers to the dependent variable. Estimates are for unreserved seats only. Robust standard errors clustered by running variable in parentheses. Anderson (2008) q-values in square brackets. Bandwidth is reported in female literacy rate percentage points around treatment cut-off of 39.3 percent. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.10$.