Female Politicians and Female Entrepreneurship

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Abstract

We study the impact of electing female political leaders on female entrepreneurship. Using a regression discontinuity design (RDD) to examine US mayoral elections between 1970 and 2020, we find that female-founded startups as well as startups with a diverse founding team increase significantly following the election of a female mayor in a given city. While the increase in female startups is greater in larger cities, it is not exclusive to cities in California or Massachusetts. Furthermore, we show that government grant-based funding for women-founded startups increases significantly in the post-election period. Given the recent anecdotal trends that female entrepreneurs start businesses in FemTech industries promoting female health and well-being, our paper suggests that female political power can empower female entrepreneurship and reduce gender-based health inequality.

JEL-Classifications: G24, G30

Keywords: Gender-based gaps in politics and entrepreneurship, female entrepreneurs, female politicians, diverse and minority-founded startups, FemTech industries, gender-based health inequality.

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1 Introduction

Women are massively underrepresented in business leadership positions, politics, and entrepreneurship. International female parliamentary representation stands at 26% in 2023.[1] Women represent less than 20% of board of directors and only 5% of CEOs at S&P 500 firms (Adams and Ferreira, 2009). Women representation in entrepreneurship is even more rare. Women-founded startups represent less than 3% of all venture capital (VC)-backed startups and women account for less than 15% VC investors (Snellman and Solai, 2022). The percentage of VC funding received by female-led startups in the US fell from 2.4% in 2021 to 1.9% in 2022. But it increased to 17.2% if the management team of the startup included at least one man.[2] The dominance of men as both VCs and founders of VC-backed startups gives rise to a vicious cycle: male VCs invest in male-founded startups and generate massive financial gains at the exit, enabling male founders and male VCs to invest again.

An important but largely understudied mechanism for reducing the gender-based gap in entrepreneurship could be empowering women into political positions. Given the rich literature documenting the importance of politicians and political connections in investment, growth, and performance profile of mature firms (Fisman, 2001; Faccio, 2006), it is natural to expect that politicians may play an important role in the creation, financing, and growth of small entrepreneurial firms as well. Hence, we ask whether electing female political leaders supports and promotes female entrepreneurship in the elected leader's city. To the best of our knowledge, this is the first study that examines whether female politicians empower female entrepreneurs.

Specifically, we analyze how the number of female-founded firms changes subsequent to elections of female mayors in US cities. To address endogeneity concerns, we employ a regression discontinuity design (RD) to investigate close mayoral elections between female and male mayoral candidates. Our identification strategy compares female startup creation in cities where female mayors won by a narrow margin with female startup creation in cities where male mayors narrowly won. Because such narrowly won elections provide quasi-random variation in election winners, whether or not a female candidate wins the election depends to a large extent on chance and idiosyncratic factors unlikely to be fundamentally related to the entrepreneurship potential of the city.

Our data on mayoral elections come from Ferreira and Gyourko (2009) and ourcampaigns.com. Merging these two datasets leads to a dataset of 10,000 mayoral elections in roughly 1,100 U.S. cities between 1945 and 2020. It contains information on the name, vote share and party affiliation of the winner and runner-up candidates. The election dataset is limited to cities with more than 10,000 inhabitants as of the year 2000. We also collect information on the gender of the top two candidates. We use the list of common first names provided by the U.S. Census and then use a machine-learning algorithm provided by Namsor.com to identify candidates' gender.[3]

Our data on startups come from Crunchbase which is a leading open-source database on early-stage startup dynamics and their fundraising outcomes. It provides firm-level information on the founding date, the identity of the founders including gender and race, industry, and

[1] Source: International Parliamentary Union https://data.ipu.org/content/parline-global-data-national-parliaments

[2] Source: Financial Times, March 8, 2023

[3] For ambiguous first names we manually check mayoral candidates.

employment categories. We aggregate all startups by their founding date at the city level and merge them with the election data. As of 2022, our sample has 436,885 total startups, 18,353 diverse startups, and 16,465 women-founded startups.

Our results show that narrowly electing female mayors increases the share of female-founded startups by roughly 1.2 percentage points in the post-election period relative to the set of cities where male candidates narrowly won. Given a mean share of female startups of 2.05% and a standard deviation of 7.4, this effect translates into a 50% increase relative to the mean or 16% increase in terms of the standard deviation. We also find that electing a female mayor results in an increase in the number of diverse startups where diverse startups are defined as those founded by either a woman, an African-American, an Asian, Hispanic, Native Hawaiian, or Middle Easterner in the respective city. Furthermore, we investigate how the effects of female political leadership evolve over time and find that RD treatment effects become statistically significant after the second year of the post-election period.

The positive impact of female politicians on female entrepreneurship is not exclusive to cities in California and Massachusetts. The effect exists in cities outside existing entrepreneurial hubs, suggesting that women in politics could be a mechanism for promoting female entrepreneurship in mainland America - arguably where it is needed most. Similarly, the impact of female politicians on female startup activity is stronger in larger cities, although it does not vary with the wealth level in the city.

One plausible explanation for our main finding is that would-be female entrepreneurs expect that with a female mayor in power in their city, it would be easier to access capital for founding their startup. Local politicians may have power in allocating government funds, subsidies and tax reductions to local startups. Female mayors may have greater preference for promoting female entrepreneurship and hence, may be more willing to provide startup financing to female entrepreneurs. Second, to the extent that local politicians are likely to be connected to local banks and existing established firms, they may be instrumental in helping female entrepreneurs raise capital from local banks and local established firms. Government grants and bank loans raised, in turn, could facilitate female-founded startups' access to other sources of capital such as venture capital funding (Howell, 2017). In anticipation of greater availability of startup financing, would-be female entrepreneurs may have greater willingness to start new businesses subsequent to election of female mayors. Consistent with the availability of and access to funding channel, we find that government grants received by female-founded startups increase significantly in cities where female mayors get narrowly elected.

Our paper contributes to the emerging literature on female entrepreneurship. It suggests that gender-based gap in politics and gender-based gap in entrepreneurship are related, and efforts to narrow the former likely help narrowing the later. Ewens and Townsend (2020) finds that male investors show less interest in female entrepreneurs while female investors express more interest in female entrepreneurs. This finding is consistent with the premise of our paper that female politicians may express greater interest in promoting female founders. Using French administrative data, Hebert (2020) finds that female-founded startups are 18% less likely to raise external equity financing. The gender funding gap reverses in female-dominated industries where female founders are more likely to raise funding than male entrepreneurs. Our paper proposes that one way to mitigate the gender funding gap could be to reduce the gender-based gap in politics. Snellman and Solai (2022) finds that female founded startups which raised funding from female rather than male VCs are two times less likely to raise subsequent financing. The paper finds no equivalent investor gender effect for male-founded firms, suggesting that initiatives encouraging women VCs to invest in women might negatively affect the long-term success of female entrepreneurs. Fairlie et al. (2020) find that black founders face greater difficulty in raising external capital, especially bank debt.

Our paper is also related to the rich literature establishing importance of political connections for established mature firms. Goldman et al. (2009) finds that the announcement of the board nomination of a politically connected director results in a positive abnormal stock return for the firm nominating the director. Goldman et al. (2013) examines the change in control of both House and Senate following the 1994 election in the US and finds that firms with board connections to the winning (losing) party experience a significant and large increase (decrease) in procurement contracts after the election. Hasan et al. (2020) studies the effect of electing female mayors on financing cost of local government debt and find that yield spreads of municipal bonds issued by cities with women mayors are lower than cities with male improving municipal fiscal conditions during their term. Krause (2020) examines the effect of electing a black mayor on black households' access to mortgage and finds that mortgage lending to black loan applicants increase significantly following the election of a black mayor. Our paper contributes to this literature by showing that politicians matter for small entrepreneurial firms and reducing gender based gap in politics may help reduce gender based gap in entrepreneurship.

2 Sample and Data

Electoral data. We compile data from a number of sources. Data on mayoral elections come from Ferreira and Gyourko (2009) and ourcampaigns.com. Merging these two datasets leads to a final dataset of 10,000 mayoral elections in roughly 1,100 U.S. cities between 1945 and 2020. It contains information on the name, vote share and party affiliation of the winner and runner-up candidates. The election dataset is limited to cities with more than 10,000 inhabitants as of the year 2000. We also collect information on the gender of the top two candidates in the following way. First, we match the first names of the mayor and the runner-up candidate with a list of common first names provided by the U.S. Census, which contains gender information. Second, we use candidate names and machine-learning algorithm provided by Namsor.com to identify the gender. Namsor provides the machine-determined gender and the probability. For gender-neutral or gender-ambiguous names (*e.g.*, Blair, Tracy, Jamie), when the Namsor's probability is below 0.65, or when we have conflict gender information from different sources, we search for evidence of the person's gender via Internet searches.

Two data constraints reduce the number of observations: (i) the outcome variable is available from 1970 until 2022 and (ii) the RD design requires to analyze mixed-gender elections[4], i.e., a female candidate runs against a male candidate. This results in a regression sample with 1,549 mixed-gender elections in 709 cities that enter the RD estimation. Table 1 shows some key city characteristics of all cities in column (1). Column (2) shows city traits with population above 10,000 inhabitants as of the year 2000. Column (3) and (4) display city characteristics for the whole election and Crunchbase sample, respectively. Column (5) and (6) only look at elections where female candidates run against male candidates. Column (5) shows city characteristics for the raw mixed-gender election sample and column (6) for mixed-gender elections matched to Crunchbase. As expectedly, mixed-gender elections and startup formation occur disproportionately in the west of the U.S. and in larger cities.

– Insert Table 1 here –

Startup data. Information on startups come from Crunchbase which is a leading open-source database on early-stage startup dynamics and their funding round activities. It provides firm-level information on the founding date, the identity of the founders and business leaders including gender and race, industry and employment categories,

We aggregate all startups by their founding date at the city level and merge with the election data. As of 2022, our sample has 436,885 total startups, 18,353 diverse startups- those founded by either a woman, an African-American, an Asian, Hispanic, Native Hawaiian or Middle Easterner and 16,465 startups founded by women. Note that these numbers refer only to newly founded businesses and do not take into account whether startups exit or not. Table 2 presents

[4]The motivation behind this constraint is to compare cities where female mayoral candidates barely won with cities where female mayoral candidates barely lost. As a consequence, the RD design disregards all elections where the mayor and the runner-up have the same gender.

the average number of startups counts for the period 1970 - 2022 for all cities in panel (A) and for cities that could be matched to the election data (panel B).

– Insert Table 2 here –

3 Data and Empirical Strategy

3.1 The RD Design

Since female mayorships are not randomly assigned to U.S. cities, identifying the causal effect of female political leadership on female entrepreneurship is challenging. Comparing firm dynamic outcomes in women-governed cities with firm outcomes in male-governed cities is biased because e.g., demographic developments that are unobserved by the researcher can lead to the female candidate's victory and to higher startup creation. Cities with high support for a female mayor might be more progressive compared to male-governed cities and thereby also more conducive environment for entrepreneurship. According to Lee (2008) and Lee and Lemieux (2010), narrowly decided mixed-gender elections provide quasi-random variation in election winners because which gender type wins is likely to be determined by idiosyncratic factors as long as contestants cannot systematically manipulate the election outcome.

The RD design embodies the reasoning above by assigning the treatment (female mayorship) deterministically to those units whose running variable (female margin of victory) is above the cutoff, $c = 0$, while leaving units with vote margins below the cutoff as untreated. Female candidates with a win margin below the cut-off are assigned to the control group (male mayoralty). In the context of mixed-gender elections, the RD design holds constant the conditions that give rise to female mayoralties and thereby reduces omitted variable bias (OVB).

The RD treatment effects of female political leadership on startup creation outcomes are estimated as follows:

$$S_{c,t} = \alpha_0 + \beta_1 Female_c + P(\gamma, margin_c) + X_c^{'}\tilde{\delta} + \epsilon_{c,t} \tag{1}$$

where $S_{c,t}$ represents the share of diverse or women-founded startups in city c in year t during the post-election period, which lasts for the duration of a mayor's first term.[5] The variable $Female_c$ is a dummy with value one in each year of the first term indicating whether the female candidate won the mayoral election in city c and zero if the female candidate lost the mayoral race. The running variable $margin_c$ is the female vote margin of victory, defined as the vote percentage obtained by the female candidate minus the percentage obtained by its strongest male opponent. P is the polynomial order of the vote margin depending on the selection procedure by Pei et al. (2022). $\epsilon_{c,t}$ is an idiosyncratic error. Standard errors are clustered at the city level. We estimate equation (1) non-parametrically by using the `rdrobust` package of Calónico et al. (2014) and report RD point estimates with robust standard errors.

We further estimate dynamic RD treatment effects by following Cellini et al. (2010):

$$S_{c,t,\tau} = \theta_\tau Female_{c,t} + P(\beta_\tau, margin_c) + \gamma_{c,t} + \epsilon_{c,t,\tau} \tag{2}$$

[5] The choice of a mayor's term duration for the outcome variable is motivated by Dell (2015). For every city, we pool yearly startup outcomes over the respective term length after the focal election date. In our sample, 78% of cities have a 4-year term length, 2% of cities have a 3-year term length and 20% a 2-year term of office.

where $S_{c,t,\tau}$ represents the startup formation outcome for city c in the election year t and the number of years elapsed between the election date and the date the outcome was measured τ. $Female_{c,t}$ is a dummy variable equal to one if city c elected a female mayor in year t and zero if the female candidate lost the election. The running variable $margin_{c,t}$ is the female vote margin of victory, defined as described above. P stands for a N-order polynomial in the vote share to control for different functional forms in the assignment variable according to Pei et al. (2022). We include election FE ($\gamma_{c,t}$) that absorbs any across-city variation. $\epsilon_{c,t,\tau}$ is an idiosyncratic error term. We cluster standard errors at the city-level.

As we analyze count-like outcome variables (number of startups or funding amounts), we are faced with a right-skewed distribution with a masses of zero values. Even estimating linear regressions with a $log(1+x)$ transformed outcome variable might bias our estimates and cause a wrong sign in expectation. Thus, we follow Cohn et al. (2022) and use a Poisson estimator for the dynamic RD treatments effects. Specifically, we use the Poisson pseudo-likelihood regression estimator Stata package `ppmlhdfe`.[6]

Bandwidth, polynomial order, and inference. To conduct the formal RD analysis, we estimate RD treatment effects via local polynomial nonparametric methods in a neighborhood, h, around the cutoff using robust bias-corrected confidence intervals Calónico et al. (2014). The optimal bandwidth h^* is calculated using the MSE-optimal bandwidth-selection algorithm developed by Calonico et al. (2019) for each of the baseline outcomes separately and including covariates. The polynomial order of the assignment variable is based on the selection procedure developed by Pei et al. (2022).[7] Since this bandwidth-selection algorithm is a data-driven approach, each outcome variable produces a different bandwidth. We employ a triangular Kernel scheme that gives more weight to observations close to the cutoff. All results are insensitive to applying alternative weighting schemes such as a uniform kernel or the Epanechnikov kernel.

Covariates. To increase the precision of the RD estimates, we include predetermined control variables denoted by X_c'. City-level covariates come from the U.S. Census and contain: the population count in thousand of persons, the share of female population, the share of the population with a college degree, the share of married females, the share of people with income below the poverty line, the share of black population, the share of people under age 18 and the log of median household income.

[6]Unfortunately, the static RD estimator by Calónico et al. (2014) does not allow for Poisson regression. We therefore take the dynamic RD estimates as conservative benchmark.

[7]Although low-order (linear) polynomial approximation is substantially more robust and less sensitive to boundary and overfitting problems (Cattaneo and Titiunik, 2022), we follow Pei et al. (2022) and use the estimated asymptotic mean squared error as optimality criterion for determining the polynomial order.

4 Results

Density of the running variable. A standard validity check in the RD literature tests for discontinuity of the assignment variable around the cut-off (Imbens and Lemieux, 2008). Intuitively, a discontinuous jump of female candidates' vote shares around zero might indicate that certain candidates have a systematic advantage or differential resources to influence the outcome and self-select into treatment. This endogenous sorting around the threshold would seriously threaten internal validity. Figure 1 shows no statistically significant discontinuous jump of the assignment variable. In addition, the density test by Cattaneo et al. (2018) based on local polynomial density estimation technique yields a p-value of 0.27 failing to reject the null hypothesis of no difference in the density of treated and control observations around the cut-off.

Covariate balance. Table 4 shows the covariate continuity test for the global and local samples indicating no discontinuities for all city level controls as indicated by the RD estimates and the corresponding p-value in column (2) and (3), respectively. Since U.S. Census data come in decennial frequency, we use the most recent pre-treatment values as controls.[8] Referencing the covariates to the election year is motivated by the fact that RD designs should include only covariates that are unaffected by the treatment Lee and Lemieux (2010).

– Insert Table 4 here –

RD results. This section presents the nonparametric local estimation results for the RD treatment effects of female political leadership. Table 5 presents the RD regression results of the baseline scenario. All dependent variables are pooled across years within the first mayoral term. The first column estimates RD treatment effects for the global sample with a cubic functional form of the assignment variable that mimic the top two graphs in figure 2. The remaining columns perform local linear RD regressions using MSE-optimal bandwidths (Calonico et al., 2019) without covariates (Column (2)) and including covariates (Columns (3)). As expected, adding covariates does not substantially change the magnitude of the point estimates for both outcome variables.

All columns show positive and statistically significant treatment effects on startup creation. Narrowly electing female mayors increases the share of diverse and women startups by roughly 1.2 percentage points in the post-election period. Given a mean share of diverse startups of 2.05% and a standard deviation of 7.4, this effect translates into a 50% increase relative to the mean or 16% increase in terms of the standard deviation.

– Insert Table 5 here –

Dynamic RD results. In this section, we examine the effect of female mayors on female-founded startup creation in each of the four years following the election of the female mayor.

[8] The robustness of results are unaffected if we follow Vogl (2014) and linearly interpolate between census years.

To the extent that it takes time for a would-be female entrepreneur to start a business after observing the election of a female mayor, we expect the female mayor effect to become stronger in the long run. Figure 3 confirms this conjecture. The effect of narrowly electing a female mayor on diverse and female startup creation becomes stronger and statistically significant two years after the election of the mayor. Given the findings in the extant literature on serial startups and startup entrepreneurs turning into venture capital investors for future startups, it is plausible to expect that political empowerment of women would have a persistent effect on female startups, and hence likely to contribute to narrowing of the gender-based gap in entrepreneurship and business. In future work we plan to use the recursive and one-step RD estimator by Cellini et al. (2010) to check the long-term effects of female political leadership beyond the first mayoral term.

– Insert Figure 3 here –

5 Robustness.

Party Affiliation. Since female politicians tend to self-select themselves more into the Democratic party, our baseline effects could be driven by party affiliation. To address this concern, we re-run the dynamic RDD specification on two sub-samples: (1) elections where female and male candidates share the same party affiliation versus (2) elections where candidates have an opposite party affiliation. If party affiliation of the politician drives our effects, then our negative RD treatment effect should not hold in the "same-party" sub-sample. We present the estimation results in Figure A1. Interestingly, we find that the RD treatment of female mayor is more pronounced in elections where female and male candidates share the same party affiliation. Hence, we conclude that our baseline results are not driven by a partisan effect.

Bandwidth sensitivity. As the empirical findings are usually quite sensitive to the choice of bandwidth Imbens and Lemieux (2008), Table A1 shows the robustness of the RD treatment effects based on four different bandwidths. Intuitively, increasing the bandwidth will decrease the variance, and so the size of the confidence intervals, but increase the bias of the estimator. The sensitivity test re-estimates RD treatment effects for a range of bandwidths smaller and larger than the optimal bandwidth h^* in 0.1 intervals between 0.03 to 0.33. Table A1 suggest that the RD point estimates broadly remain statistically significant in a neighborhood around the optimal bandwidths for both outcome variables.

6 Mechanisms.

This section explores the potential mechanisms behind our main finding. From a theoretical perspective, gender should not matter for policy outcomes if politicians cater to the preferences of the median voter (Downs, 1957). In contrast, the citizen candidate model predicts that specific candidates care about implementing a better policy for their respective constituencies above and beyond maximizing their popularity (Besley and Case, 2003; Alesina, 1988). Given the well-documented gender gap in entrepreneurship and corporate finance, we hypothesize that female politicians care about the empowerment of female entrepreneurs.

Access to Funding. To test whether female politicians may take an active role in facilitating female-founded startups' access to government grants, we extract information on government grants received by each startup at each capital raising rounds from Crunchbase. We not only know the exact dollar amount of government grants received but also the exact date, and the startup receiving the grant. We collapse government grant flows at the city-year level and distinguish by firm type (all startups, diverse, and women-founded startups). Figure 4 shows the dynamic RD treatment effects based on equation (2).

– Insert Figure 4 here –

The effects of female political leadership on government grants received by women-founded and diversity startups are statistically significant in the first year of the post-election period. This result is consistent with the interpretation that women mayors facilitate women entrepreneurs' access to government grants. Initial grants received could then facilitate further equity financing from venture capitalists, consistent with the evidence in Howell (2017).

City characteristics. To rule out that our baseline result is driven by particular regions with a large concentration of startup dynamism we drop the state of California and Massachusetts. Column (2) of Table (6) shows that omitting these two states from the sample does not change the statistical significance and even increases the point estimates.

7 Conclusion and outlook

Women are massively underrepresented in politics and entrepreneurship. In fact, World Economic Forum identifies economic participation and politics as two major areas with the most significant gender-based gaps [9]. In this paper, we propose that gender-based gaps in politics and entrepreneurship are closely related, and empowering female politicians may help empower female entrepreneurs.

Specifically, we study the impact of electing female political leaders on female-founded startups. We find that female-founded startups as well as startups with a diverse founding team increase significantly following the election of a female mayor in a given city. Importantly, this effect exists in cities outside California and Massachusetts, suggesting that female politicians could be instrumental in promoting female entrepreneurship in mainland America. We also find that government grants received by female-founded startups increase significantly in cities with an elected female mayor in the post-election period. Our results are consistent with female mayors providing more attention and support to female founders, increasing their access to capital. Overall, our paper suggests that female political power can empower female entrepreneurship, with real benefits to the local economy. In addition, given the recent anecdotal evidence that female-founded startups are more likely to be in FemTech industries promoting women's health and well-being, reducing gender-based gap in entrepreneurship likely reduces gender-based health inequality, further empowering women's participation in politics and entrepreneurship.

[9] Source: World Economic Forum, Gender Inequality, July 13, 2022

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Tables and Figures

Table 1: Sample representativeness.

	Cities					
	All	> 10,000	Elections	Startup	Male vs. Female	
					Non-startup	Startup
	(1)	(2)	(3)	(4)	(5)	(6)
Population	7,496	41,545	87,768	88,883	105,055	107,059
Median Family Income	45,670	55,564	51,600	51,481	52,026	51,934
Median House value	98,947	146,111	136,762	136,978	140,705	140,869
% Homeownership	65	61	57	57	56	56
% Black	7	11	12	12	13	13
% under 18	26	25	26	26	26	26
% Poverty Share	13	11	13	13	13	13
% Female Married	45	43	41	41	40	40
% Coll Female	8	11	10	10	10	10
% Labor	47	50	50	50	50	50
% Labor Female	43	46	46	46	46	46
% West	17	19	26	26	27	28
% South	29	23	21	21	23	23
% Midwest	29	15	28	27	27	26
% Northeast	13	12	13	13	14	14
Nr Cities	34,230	12,634	1,116	1,041	751	709

Note: This table shows mean city characteristics for different city categories. Column (1) depicts all US cities and column (2) cities with more than 10,000 people as of year 2000. Column (3) shows cities with election information and column (4) cities that are captured in Crunchbase. The last two columns present cities where male candidates ran against female mayoral candidates. Column (5) presents city characteristics of the raw set of mixed-gender elections and column (6) of mixed-gender election cities that could be matched to Crunchbase.

Table 2: Matching Crunchbase and election data.

Variable	Obs	Mean	SD	Min	Max	Cities
(A) Total crunchbase sample						
Startups (all)	159,726	4.64	27.85	1	2,354	1,041
Startups (diverse)	159,726	0.16	3.10	0	315	1,041
Startups (women)	159,726	0.15	2.79	0	290	1,041
(B) Matched sample						
Startups (all)	27,019	14.70	65.44	1	2,354	709
Startups (diverse)	27,019	0.65	7.40	0	315	709
Startups (women)	27,019	0.58	6.64	0	290	709

Note: This table compares the raw Crunchbase dataset with the matched-election dataset and shows the number of total, diverse, and women founded startups aggregated at the city-year level.

Table 3: Summary statistics

	Obs.	Mean	Median	Std.Dev.	Min.	Max.
(A) Start-up outcomes						
All start-ups (nr.)	5,424	18.20	4.00	60.15	0	1,324
Diverse start-ups (nr.)	5,424	0.65	0.00	4.93	0	189
Women start-ups (nr.)	5,424	0.57	0.00	4.14	0	148
Diverse start-up share (%)	5,424	1.38	0.00	5.91	0	100
Women start-up share (%)	5,424	1.26	0.00	5.74	0	100
Grant-funding share (%)	4,246	1.76	0.00	7.37	0	100
Grant-funding share women SU (%)	4,246	0.14	0.00	1.68	0	50
(B) City-level data						
Female margin of victory	1,716	-0.03	-0.03	0.35	-1.00	1.00
Population (tsd. persons)	1,716	154.76	67.44	271.32	10.14	3898.75
% Female population	1,716	51.22	51.33	2.03	34.27	64.37
% College degree	1,716	16.15	14.08	9.14	1.28	54.09
% Female married	1,716	40.02	40.65	6.69	17.17	65.71
% Black	1,716	13.01	6.70	15.73	0.00	98.10
% Poverty	1,716	13.07	12.53	7.09	1.08	45.11
% under 18	1,716	25.27	25.08	5.65	5.76	48.86

Note: Panel A presents the summary statistics of the start-up data. Each observation corresponds to start-ups founded in year t of the first term of the mayor in the city c where the focal election takes place. Diverse start-ups are defined as any firm that is founded by either a women, an African-American, an Asian, Hispanic, Native Hawaiian or Middle Eastern person in the first mayoral term in the respective city. Women start-ups are founded by female entrepreneurs. The share of diverse and women start-ups are defined in relation to total start-ups in year t in city c. Panel B presents the summary statistics of the city level data. Female win margin is defined as the difference in the vote share of the female candidate and the vote share of the male competitor. A negative margin indicates an electoral defeat of the female candidate and a positive margin indicates an election victory of the female mayoral candidate. The poverty rate is defined as persons below poverty level over total persons.

Table 4: Covariate continuity test

	Bandwidth	RD_bc	Pval	CI low	CI high
	(1)	(2)	(3)	(4)	(5)
		(A) Global sample, p=4			
Population (1,000 persons)	1.00	30.21	0.29	-25.87	86.28
% female population	1.00	-0.04	0.91	-0.82	0.73
% college degree	1.00	-0.29	0.88	-4.02	3.45
% married females	1.00	0.37	0.76	-1.99	2.73
% under 18	1.00	-0.28	0.79	-2.38	1.82
log(median hh income)	1.00	-0.04	0.69	-0.24	0.16
% poverty	1.00	-0.90	0.53	-3.68	1.89
		(B) Local sample, p=1			
Population (1,000 persons)	0.19	27.27	0.26	-20.13	74.67
% female population	0.18	0.01	0.97	-0.71	0.74
% college degree	0.29	0.41	0.78	-2.43	3.25
% married females	0.23	0.55	0.59	-1.42	2.52
% under 18	0.27	-0.21	0.80	-1.83	1.40
log(median hh income)	0.25	-0.03	0.70	-0.19	0.13
% poverty	0.25	-1.32	0.24	-3.51	0.86

Note: This table presents a formal falsification test on how balanced city-level covariates are around the election cutoff. Each covariate is measured in the election year and is regressed separately on the running variable via the `rdrobust` command for the global sample in Panel A and the local sample in Panel B using the MSE-optimal bandwidth. Column (2) shows the local linear RD treatment estimate with robust bias-corrected confidence intervals in columns (4) and (5) and the corresponding p-value in column (3).

Table 5: RD estimates - Start-ups

	(1)	(2)	(3)
	(A) Diverse start-ups (%)		
Female win	0.989**	0.895*	0.807*
	(0.47)	(0.49)	(0.49)
Obs	5,424	3,106	3,106
CCT Bandwidth	1	0.24	0.24
# Elections	1716	967	967
Polynomial order	3	1	1
	(B) Women start-ups (%)		
Female win	1.029**	0.920*	0.856*
	(0.46)	(0.49)	(0.49)
Obs	5,424	3,059	3,059
CCT Bandwidth	1	0.23	0.23
# Elections	1716	950	950
Polynomial order	3	1	1
City Covs	No	No	Yes

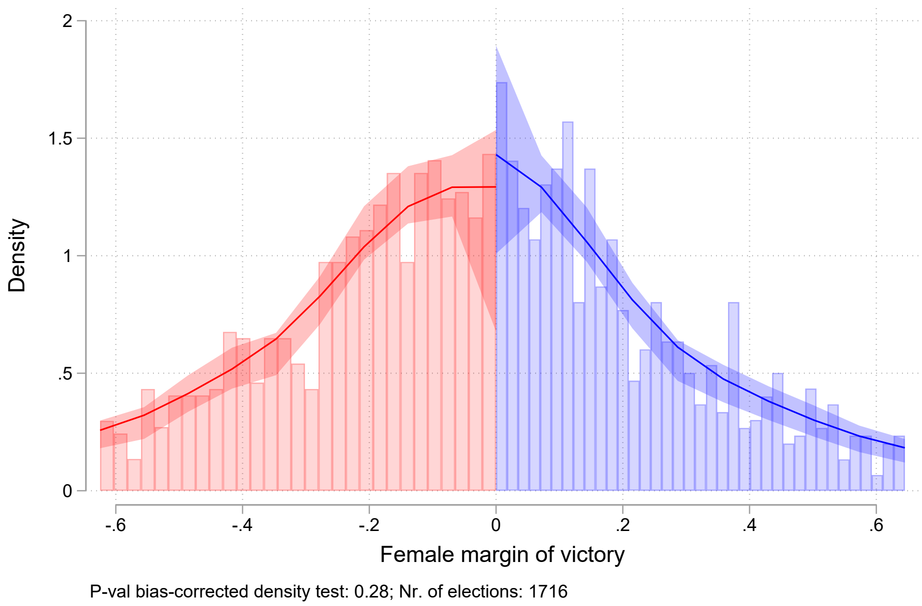
Note: This table presents RD treatment effects with robust bias-corrected confidence intervals using the `rdrobust` Stata command. The assignment variable is the female win margin defined as the difference in the vote share of the female candidate and the vote share of the male competitor. The polynomial order describes the functional form of the assignment variable determined via Pei et al. (2022). The first dependent variable in panel A is the share of diverse startups to total startups. Diverse startup is defined as a firm that is founded by either a women, an African-American, an Asian, Hispanic , Native Hawaiian or Middle Eastern person in the first mayoral term in the respective city. The second outcome variable in panel B is the share of women founded startups to total startups. Column (1) shows RD treatment effects for the global sample with a cubic functional form of score. Column (2) and (3) display local linear RD estimates based on the optimal bandwidth (CCT) calculated by the mean-squared-error (MSE) optimal bandwidth selector (Calonico et al., 2019) with and without city-level covariates. Standard errors are in parentheses and refer to heteroskedasticity-robust nearest neighbor variance estimation with a minimum of three matches. City-level covariates are measured in the election-year and consist of: ln(population), share of female persons to total persons, share of married women, poverty rate, share of persons younger than 18, and ln(median household income). ***p < .01, **p < .05, *p < .1 .

Table 6: RD estimates - Heterogeneity

	Base-line	Excl. CA/MA	Small Cities	Large
	(1)	(2)	(3)	(4)
	(A) Diverse start-ups (%)			
Female win	0.812*	0.909*	0.507	0.965*
	(0.49)	(0.55)	(0.84)	(0.54)
Obs	3,130	2,552	1,615	1,515
CCT Bandwidth	0.24	0.24	0.24	0.24
# Elections	974	777	515	459
Polynomial order	1	1	1	1
	(B) Women start-ups (%)			
Female win	0.864*	0.975*	0.557	1.014*
	(0.49)	(0.55)	(0.84)	(0.54)
Obs	3,059	2,506	1,588	1,471
CCT Bandwidth	0.23	0.23	0.23	0.23
# Elections	950	764	504	446
Polynomial order	1	1	1	1
City Covs	Yes	Yes	Yes	Yes

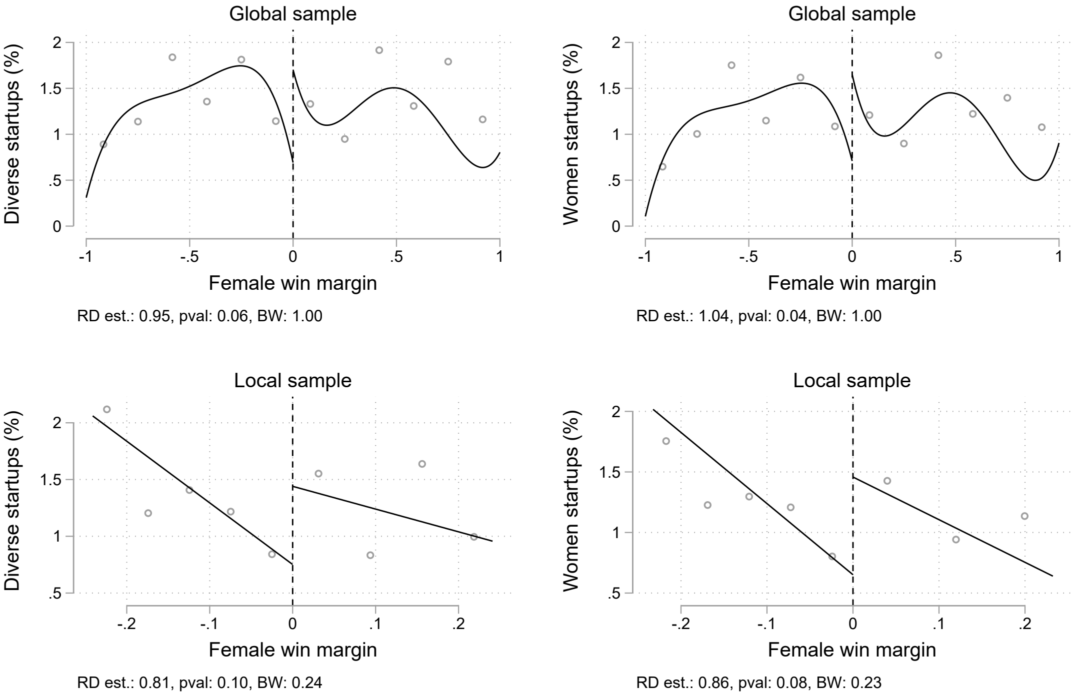
Note: This table presents RD treatment effects with robust bias-corrected confidence intervals using the `rdrobust` Stata command. The assignment variable is the female win margin defined as the difference in the vote share of the female candidate and the vote share of the male competitor. The polynomial order describes the functional form of the assignment variable determined via Pei et al. (2022). The first dependent variable in panel A is the share of diverse startups to total startups. Diverse startup is defined as a firm that is founded by either a women, an African-American, an Asian, Hispanic , Native Hawaiian or Middle Eastern person in the first mayoral term in the respective city. The second outcome variable in panel B is the share of women founded startups to total startups. Column (1) shows RD treatment effect for the baseline scenario. Column (2) replicates the baseline without without California and Massachusetts. Column (3) and (4) display local linear RD estimates for small versus large cities. Small (large) cities are defined as having a population count below (above) the median population. Standard errors are in parentheses and refer to heteroskedasticity-robust nearest neighbor variance estimation with a minimum of three matches. City-level covariates are measured in the election-year and consist of: ln(population), share of female persons to total persons, share of married women, poverty rate, share of persons younger than 18, and ln(median household income). ***p < .01, **p < .05, *p < .1 .

Figure 1: Validity Test



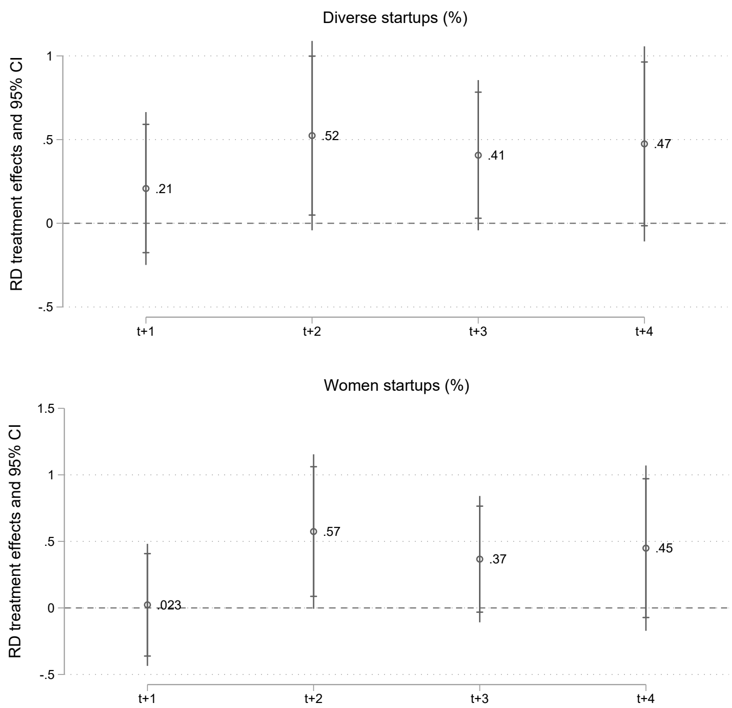
Notes: This graph shows the distribution of the assignment variable for mixed-gender elections. The assignment variable is the female win margin with the cut-off being at zero. A negative margin indicates that a female candidate lost the mayoral election, while positive values represent an election victory. The bars constitute the histogram of the female win margin. Solid lines represent a local polynomial density plot of the female vote margin with 95% confidence intervals. The bias-corrected density test is conducted by the `rddensity` command.

Figure 2: Regression Discontinuity Plot.



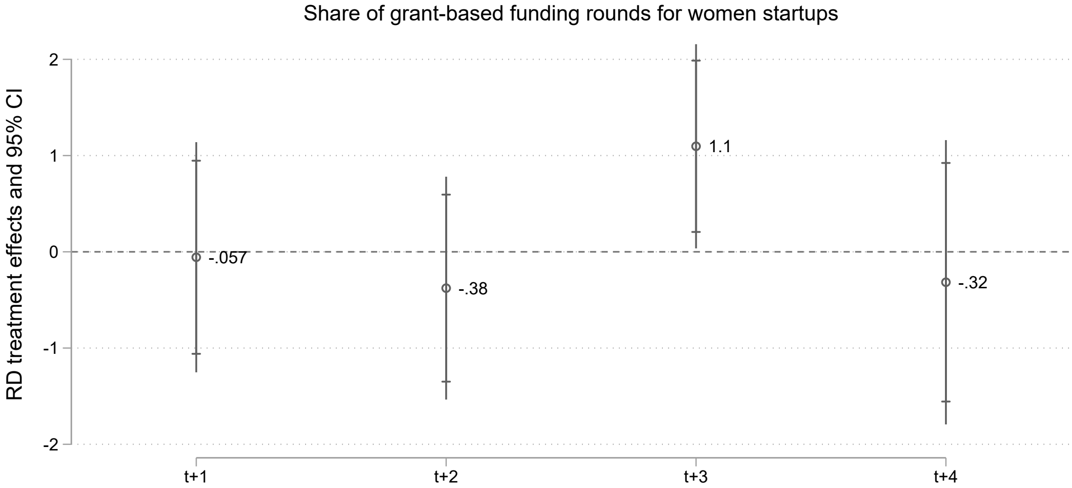
Notes: This RD graph plots startup outcome variables against the female vote margin of victory. A negative margin indicates that a female candidate lost the mayoral election while positive values represent an election victory. Each of the dots is the average value of the outcome in vote margin bins. The number of bins is determined by the IMSE-optimal evenly spaced method of the `rdplot` command. The outcome variables is the share of diverse and women founded startups to total startups during the first mayoral term. The solid black lines in Panels (a) and (b) are fourth-order global polynomial fits using the raw data and linear fits for Panels (c) and (d). RD estimates with corresponding robust p-values and bandwidth are displayed below each subgraph.

Figure 3: Dynamic RD treatment effects



Notes: This figure presents the parametric local linear RD treatment effects for each year of the mayoral term. Each dot is the point estimate of estimating equation (2). The outcome variables is the share of diverse and women founded startups to total startups during the first mayoral term. The specification includes election fixed effects, clusters standard errors at the city level and uses the Poisson pseudo-likelihood regression estimator `ppmlhdfe`. Bars (whiskers) span the 95(90)% confidence interval, respectively.

Figure 4: Female mayors and startup funding



Notes: This figure presents the parametric local linear RD treatment effects for each year of the mayoral term. Each dot is the point estimate of estimating equation (2). The outcome variable is the share of grant-based funding rounds to the total number of funding rounds going to female startups in the respective year during the first mayoral term. The specification includes election fixed effects, clusters standard errors at the city level, and uses the Poisson pseudo-likelihood regression estimator `ppmlhdfe`. Bars (whiskers) span the 95(90)% confidence interval, respectively.

Appendix

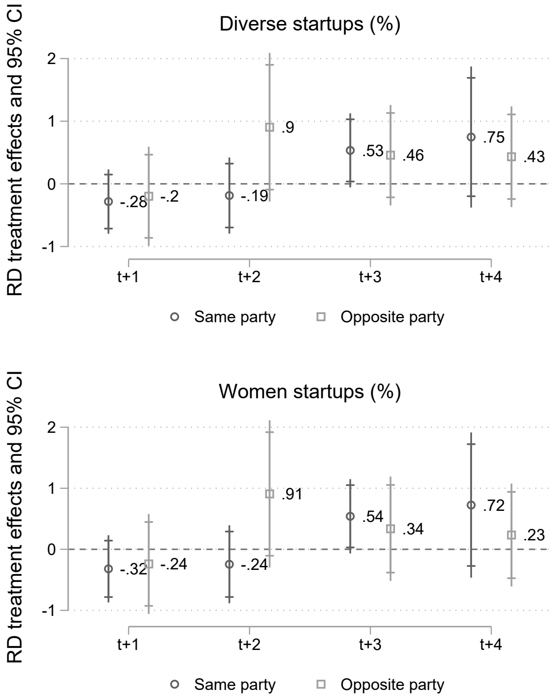
A1 Figures and Tables

Table A1: RD estimates - Sensitivity

	(1)	(2)	(3)	(4)
	(A) Diverse start-ups (%)			
Female win	1.099**	0.588	0.920*	0.804*
	(0.50)	(0.50)	(0.50)	(0.46)
Obs	482	1,914	3,037	3,763
Bandwidth	0.03	0.13	0.23	0.33
# Elections	151	594	944	1174
Polynomial order	1	1	1	1
	(B) Women start-ups (%)			
Female win	1.089**	0.678	0.931*	0.852*
	(0.50)	(0.50)	(0.49)	(0.45)
Obs	482	1,914	3,037	3,763
Bandwidth	0.03	0.13	0.23	0.33
# Elections	151	594	944	1174
Polynomial order	1	1	1	1
City Covs	Yes	Yes	Yes	Yes

Note: This table presents RD treatment effects with robust bias-corrected confidence intervals using the `rdrobust` Stata command. The assignment variable is the female win margin defined as the difference in the vote share of the female candidate and the vote share of the male competitor. The polynomial order describes the functional form of the assignment variable determined via Pei et al. (2022). The first dependent variable in panel A is the share of diverse startups to total startups. Diverse startup is defined as a firm that is founded by either a women, an African-American, an Asian, Hispanic, Native Hawaiian or Middle Eastern person in the first mayoral term in the respective city. The second outcome variable in panel B is the share of women-founded startups to total startups. Columns (1) to (4) shows RD treatment effects for different bandwidths. Standard errors are in parentheses and refer to heteroskedasticity-robust nearest neighbor variance estimation with a minimum of three matches. City-level covariates are measured in the election year and consist of: ln(population), share of female persons to total persons, share of married women, poverty rate, share of persons younger than 18, and ln(median household income). ***p < .01, **p < .05, *p < .1 .

Figure A1: Party affiliation check



Notes: This graph shows dynamic RD treatment effects on the share of diverse and women startups for each year in the post-election period based on two subsamples. The first subsample considers mixed-gender election where candidates share the same party affiliation. The second subsample analyzes mixed-gender election where candidates are from the opposite party. The specification includes election fixed effects, clusters standard errors at the city level and uses the Poisson pseudo-likelihood regression estimator `ppmlhdfe`. Bars (whiskers) span the 95(90)% confidence interval, respectively.