# 6 Appendix A (for online publication)

## 6.1 Constructing the variable of *candidate differentiation*

### 6.1.1 Bayesian updating

In this section, we provide the intuition behind the Bayesian update approach that we have introduced in *Step 3* when constructing our variable. Consider the example that follows. In a country at time $t$, we have: a) $m$ men and $f$ women, with $m < f$, and b) certain individuals are named Billie. The number of men named Billie is denoted by $B^m$ and the number of women named Billie is denoted by $B^f$. The probability that a randomly chosen Billie is a man, $b^m$, is thus given by:

$$b^m = \Pr(man|Billie)_t = \frac{\Pr(man\ and\ Billie)}{\Pr(Billie)} = \frac{B^m/(m+f)}{(B^m+B^f)/(m+f)} = \frac{B^m}{B^m+B^f}.$$

Consider now that at time $t+s$ in a certain district $d$ of the country the number of men is $m' = a \times m$ for some $\alpha \in \mathbb{R}_{++}$ and the number of women is $f' = b \times f$ for some $b \in \mathbb{R}_{++}$, but the proportion of Billies within each gender group is identical to the country-level proportion at time $t$. That is, if the number of men named Billie in district $d$ at time $t+s$ is denoted by $B^{m'}$ and the number of women named Billie in district $d$ at time $t+s$ is denoted by $B^{f'}$, then $B^{m'} = a \times B^m$ and $B^{f'} = b \times B^f$. It follows that the probability that a randomly chosen Billie from district $d$ at time $t+s$ is a man is given by:

$$\Pr(man|Billie)^d_{t+s} = \frac{\Pr(man\ and\ Billie)^d_{t+s}}{\Pr(Billie)^d_{t+s}} = \frac{B^{m'}/(m'+f')}{(B^{m'}+B^{f'})/(m'+f')} = \frac{aB^m}{aB^m+bB^f} = \frac{ab^m}{ab^m+b(1-b^m)}.$$

If we denote the country-level share of men at time $t$ by $\tilde{m} = \frac{m}{m+f} \implies \frac{m}{f} = \frac{\tilde{m}}{1-\tilde{m}}$; and the share of men at district $d$ at time $t+s$ by $\tilde{m}_s = \frac{m'}{m'+f'} = \frac{am}{am+bf}$, we get that $b = \frac{m}{f}\frac{a(1-\tilde{m}_s)}{\tilde{m}_s} = \frac{\tilde{m}}{1-\tilde{m}}\frac{a(1-\tilde{m}_s)}{\tilde{m}_s}$ and hence that:

$$\Pr(man|Billie)^d_{t+s} = \frac{ab^m}{ab^m+b(1-b^m)} = \frac{ab^m}{ab^m+\frac{\tilde{m}}{1-\tilde{m}}\frac{a(1-\tilde{m}_s)}{\tilde{m}_s}(1-b^m)} = \frac{\frac{b^m}{\tilde{m}}\times\tilde{m}_s}{\frac{b^m}{\tilde{m}}\times\tilde{m}_s+\frac{(1-b^m)}{1-\tilde{m}}\times(1-\tilde{m}_s)}$$

We observe that: a) when the share of men in district $d$ at period $t+s$ is equal to the original country-level share of men ($\tilde{m}_s = \tilde{m}$), then $\Pr(man|Billie)^d_{t+s} = \Pr(man|Billie)_t$; b) when the share of men in district $d$ at period $t+s$ converges to one ($\tilde{m}_s \to 1$), then $\Pr(man|Billie)^d_{t+s} \to 1$; and c) when the share of men in district $d$ at period $t+s$ converges to zero ($\tilde{m}_s \to 0$), then $\Pr(man|Billie)^d_{t+s} \to 0$. All these observations confirm that the formula takes into account all available information.

### 6.1.2 Validation check

In *Steps 1-5* we have described in detail how we have constructed our variable that measures the state-wide share of electoral constests between racially differentiated candidates. But, given that the race of each candidate was not *directly* observable, we had to follow the Bayesian updating approach –we have provided a detailed rationale behind our choice in the section above. Here, in this section, we conduct a validation exercise in order to test our estimation approach. For this purpose, we have chosen a random sample of 1,000 candidates from recent elections (post-2000) where data on a candidate's race are available online and attempted to collect data regarding their race from their promotional materials and other publicly available sources. We have managed to find data for almost 700 of these candidates, and after performing a series of tests, we have found out that our approximation technique works remarkably well: it assigned the race "white" to 82.9% of the candidate population, while in our *true sample* (of 700 candidates) 83.2% of them were actually white. That is, there is *no difference* in statistical terms. The same holds true if one is to compute similar statistics by year, state, and district.

Since we want to measure the share of electoral contests that are contested between candidates of different racial backgrounds, or the share of *differentiated contests*, at the state level, we only require that our constructed variable $P_{s,t}$ aggregates information consistently at the state level. That is, even if the probability that an electoral contest is differentiated $P_{d,s,t}$ that we assign is not accurate, for our estimator to be an *econometrically admissible* *substitute* it suffices to aggregate this information consistently at the state level. In order to check this, we conduct the following test. We take all of the possible combinations that we can form of racially differentiated groups of $n$ individuals that are randomly chosen from the group of those 700 candidates that we have sampled –and whose race and ethnicity is known to us. That is, we generate groups of $n$ individuals, where $n = \{25, 50, 75, 100\}$, such that we have 0 white and $n$ non-white candidates, then 1 white and $n - 1$ non-white candidates and so on, until we have a group with $n$ white and 0 non-white candidates. For each combination, we take 10,000 random samples of size $k$ for white candidates and size $n - k$ for non-white candidates for $k = 0, 1, ..., n$. For each sample of total size $n$, we find the true and the estimated –based on $w^i_{s,t}$ that we have constructed above– mean of how many white candidates this group has. We, then, compute the grand mean of those 10,000 sample means: Figure A.1 depicts the *estimated* versus the *actual* proportion of white candidates in the group of $n$ randomly sampled candidates when $n = 50$.[33]

[Insert Figure A.1 about here]

Strikingly, the plot is an almost perfectly straight line. That is, the estimated proportion of white candidates in the group is linearly and monotonically increasing in the true proportion, and the two variables are *effectively collinear*,[34] and, hence, the use of the estimated proportion, instead of the real one, is admissible econometrically. Moreover, recall that in the true population (across states and over time) the relevant range of the share of white candidates lies between 0.7 and 0.9. Hence, our estimates are almost identical to the true values when the actual share of white candidates in the true sample is approximately 0.8 which is, in fact, very close to the overall true proportion of whites in the overall sample. In the range that is relevant, our estimator seems to perform extremely well in aggregating the information that we need.[35] Obviously, our estimator is not perfect at the individual

[33] The results are identical when we use different sampling sizes (that is, when $n = \{25, 75, 100\}$).

[34] We need to stress here that in no way did we force this relationship to be linear, but rather it is an outcome of the sampling process.

[35] Since our intention is to use the estimated proportion (at the state level) of electoral contests between

level, but in the relevant range between 0.7 and 0.9 our estimator aggregates correctly the proportion of whites in the group of $n$ randomly selected candidates. Thus, we have every reason to feel confident that our estimated parameter $P_{s,t}$ is *a fairly accurate approximation* of the share of electoral contests (within a state in a given election year) that were contested among candidates of different racial backgrounds.[36] Moreover, as an additional robustness check, we also estimate our main econometric specification (presented in the next section) by replacing $P_{s,t}$ with the simplest possible variable that we can construct: the estimated state-wide proportion of non-white (minority) candidates that stood in state legislative elections in a particular year.[37] We have already presented those additional results in Table 3 (columns 1-3).[38]

racially/ethnically differentiated candidates in the regression, the fact that our constructed variable is a linear and increasing transformation of the true proportion of white candidates when the sample is sufficiently large ($n = \{25, 50, 75, 100\}$), as is the case in reality where in each state there are many contests, implies that our estimation approach is econometrically valid.

[36]Notice that, so far, we have argued that our constructed variable is an econometrically admissible substitute under the implicit assumption that voters have full information on the racial and ethnic identity of the candidates. But, in reality, this need not be the case. In fact, it is more likely that most voters only form perceptions on the racial or ethnic identity of a particular candidate in the same way that our estimator does: they assign a particular probability of a candidate being white (or black, or hispanic) simply by observing her name in the ballot paper –many voters might not have seen the candidates in person. If that is the case for a large proportion of voters, then our constructed variable should be better in estimating the importance of identity issues in voters' decisions even than the actual share of differentiated contests.

[37]As Figure A.1 demonstrates, in the relevant range of the true proportion of white candidates in the sampled population, our estimation technique performs outstandingly. Thus, for a large number of candidates (as is the case when we aggregate information at the state level) our estimated proportion of white candidates should be statistically indistinguishable from the true one. As a result, this much simpler variable that we have constructed should be completely *bias-free*.

[38]As indicated in Step 4, we have computed our measure of candidate differentiation by focusing on two-candidate electoral contests. Yet, one can repeat the estimation without restricting the set of candidates. In such a case, since in many races more than two candidates can compete for one (or even more than two seats in the case of MMDs), the concept of calculating the probability that an electoral race is contested between two candidates of different ethnic or racial backgrounds is a bit problematic. For this reason, we calculate instead –based on the assigned probability of being non-white $1 - w^i_{s,t}$ that we have estimated in Step 3– the state-wide proportion of non-white (minority) candidates that stood in state legislative elections in a particular election year. Figure A.2 (in this appendix, section 6.2) reports the estimates of our basic econometric specification when we replace $P_{s,t}$ –the estimated state-wide proportion of differentiated electoral contests– with our new variable detailed above.

## 6.2 Alternative measures of candidate differentiation and winning candidates

With respect to the measure of candidate differentiation, here, we perform a series of additional robustness checks –of technical nature and substantive– regarding the way we have constructed our variable that measures the state-wide proportion of ethnically or racially differentiated electoral contests ($P_{s,t}$); as stated earlier, in constructing this variable we focused on two-candidate contests. Here, we repeat the same exercise of estimating our main econometric specification (equation 2) by replacing $P_{s,t,}$ with a new variable that was constructed by taking into account all available candidate entries, even the cases where more than two candidates compete for more than one seat (as in MMDs): the state-wide proportion of non-white (minority) candidates that participated in state legislative elections in a particular election year. We present those results in Figure A.2. As one can see, our findings are robust to this alteration. That is, all the qualitative implications of our study still stand regardless of how one chooses to compute the degree of candidate differentiation.

[Insert Figure A.2 about here]

Finally, we perform two additional robustness checks in order to show that a) our results are not sensitive to arbitrary coding decisions regarding the construction of our measure of candidate differentiation and, b) the effect of candidate differentiation on redistributive outcomes (and the effective tax rate) that we document is realized via the channel of electoral competition and the outcomes it produces.

For the purposes of the first exercise, in addition to excluding candidates who received less than 1 percent, we repeat the analysis by restricting our attention –when constructing our variable of candidate differentiation– to those candidates that received more than 5, 10, or 15 percent of the vote. In other words, we focus in electoral contests where the electoral competition is more meaningful. We present those results in Table A.4 and we note that are virtually indistinguishable and qualitatively-speaking identical with our previous findings.

[Insert Table A.4 about here]

Regarding the second one, we perform two types of analyses. First, we construct our measure of candidate differentiation based only on the set of winning candidates; second, as an alternative measure inspired by the analysis above, we compute the state-wide proportion of non-white (minority) candidates that participated *and won* in state legislative elections in a particular election year, and use it instead.[39]

The reason for this distinction (between a measure of candidate differentiation based on all candidates versus just winning candidates) to be made is the following: There is an implied argument about how the candidate differentiation leads to different voter behavior that selects candidates that are more or less interested in redistribution. Given that the changes in redistribution depend on the outcome of these elections, we wonder whether it might be worthwhile to see whether the relationship also holds if the analysis is performed using the subset of victorious candidates. We present those results in Table A.5. Insofar as changes in redistribution policy must be made by the winners, it is reassuring to observe that the same relationship holds if we restrict our metric to *capture the candidate differentiation of winners* as a measure of the salience of the issue within the legislature (as opposed to the electorate at large based on the previously constructed measure using all candidates).

[Insert Table A.5 about here]

## 6.3 Bootstrapped standard errors

In the paper, we have discussed the possibility that our estimated parameter $P_{s,t}$ can be a noisy –albeit econometrically admissible– measure of the true proportion of state-wide electoral contests between different-race candidates. As a result, this additional uncertainty should be reflected on the standard errors of $P_{s,t}$ and, consequently, on the CIs of the estimated marginal effect of inequality on redistributive outcomes, which is also a function of

[39] Note that both these new metrics we have constructed using only the winning candidates are aggregated at the state level, just like our other variables, because our data set contains redistributive policy outcomes only at the state level.

$P_{s,t}$. For this reason, we re-estimate our main specification (in equation 2) using bootstrapped standard errors and we present the results in Table A.6 below. We also repeat the same exercise when calculating the marginal effect of inequality on redistribution and we present those estimates in Figures A.3 through A.8. It can be seen that our main conclusion remains qualitatively unchanged: when the state-wide share of different-race electoral contests is relatively low, an increase in income inequality leads to higher taxation and redistributive spending.

[Insert Table A.6 and Figures A.3 to A.8 about here]

## 6.4 A brief theoretical argument

Consider a simple two-candidate election such that the first candidate is characterized by a pair of elements, $(a_1, a_2) \in \mathbb{R}^2$, and the second candidate is characterized by the pair, $(b_1, b_2) \in \mathbb{R}^2$. The parameters $a_1$ and $b_1$ are the (immutable) identity parameters of the candidates, while $a_2$ and $b_2$ are their (strategically chosen) economic platforms. Each voter is characterized also by a pair of elements, $(i_1, i_2) \in \mathbb{R}^2$, which we call her bliss point: $i_1$ denotes her ideal identity of the winning candidate and $i_2$ her ideal economic policy. A voter votes for the candidate whose pair of elements is closer –in terms of Euclidean distance– to her bliss point; and evenly splits her vote in case of indifference. Let us assume that the bliss points of the society are distributed on $[-1, 1]^2$ according to twice differentiable distribution $F$ and that candidates propose $a_2$ and $b_2$ strategically trying both to attract as many votes as possible and to represent special constituencies that they are supported (or financed) from. Formally, consider that they maximize $v(a_2, b_2 : a_1, b_1, F) - w \times (a_2 - \hat{a})^2$ and $1 - v(a_2, b_2 : a_1, b_1, F) - w \times (b_2 - \hat{b})^2$ respectively, where $v(a_2, b_2 : a_1, b_1, F)$ is the vote share of the first candidate, $\hat{a}$ ($\hat{b}$) is the economic policy pursued by the constituency that the first (second) candidate represents; and $w \geq 0$ is the a parameter used to weight these two goals.

If we fix for simplicity $d/2 = -a_1 = b_1 > 0$ then:

$$v(a_2, b_2 : a_1, b_1, F) =_{[0,1]} F_1\left(\frac{(b_2-i_2)^2-(a_2-i_2)^2}{2d}|i_2 = \hat{\imath}_2\right) \times f_2(\hat{\imath}_2)d\hat{\imath}_2$$

where $F_1(x_1|x_2 = \hat{x}_2)$ is the conditional distribution of ideal identities given ideal economic policies and $f_2(x_2)$ is the density of the marginal distribution of ideal economic policies. Given this standard framework, let us investigate the incentives that, for example, the first candidate faces to deviate from a symmetric strategy profile $a_2 = b_2$. The marginal effect on her vote share from proposing greater redistribution, that is, from increasing $a_2$, is equal to $\int_{[0,1]} \frac{(i_2-a_2)F_1'(0|i_2=\hat{i}_2)}{d} \times f_2(\hat{i}_2)d\hat{i}_2$ and the marginal effect on the component of her utility that depends on constituency representation is equal to $2w(\hat{a} - a_2)$.[40] As it is evident the marginal effect on a candidates' vote share from a change in economic policy is decreasing in the degree of candidates' identity differentiation, $d$, while the marginal effect on the component of her utility that depends on constituency representation remains constant; and hence *when candidates are perceived very dissimilar in their immutable characteristics, candidates have less incentives to react to changes of voters' preferences in economic issues.* In Figure A.9 we show that this is not true only for marginal deviations, but also for non-degenerate ones. With G (L) we denote the area which contains the bliss points of the voters who start preferring the first candidate more (less) compared to the second one when the first one changes the proposed economic policy. As we see these areas become smaller as candidate differentiation in immutable characteristics becomes larger, for equal changes in the proposed economic policy of the first candidate. In other words an increasing identity differentiation between candidates should make them more interested in representing their core supporters than to propose economic policies that are attracting new voters.

[Insert Figure A.9 about here]

We do not aspire to provide a full equilibrium analysis of this model. For equilibrium analysis of multidimensional spatial models with differentiated candidates one is referred

[40]When $a_2 \neq b_2$ we have that: $\frac{\partial v(a_2,b_2:a_1,b_1,F)}{\partial a_2} = \int_{[0,1]} \frac{(i_2-a_2)F_1'(\frac{(b_2-i_2)^2-(a_2-i_2)^2}{2d}|i_2=\hat{i}_2)}{d} \times f_2(\hat{i}_2)d\hat{i}_2$. It is easy to see that as $d \to \infty$ we have $F_1'(\frac{(b_2-i_2)^2-(a_2-i_2)^2}{2d}|i_2 = \hat{i}_2) \to F_1'(0|i_2 = \hat{i}_2)$ and hence $\frac{\partial v(a_2,b_2:a_1,b_1,F)}{\partial a_2}$ converges to zero for any admissible parameter values. In other words, the marginal effect of a change in economic policy on a candidate's vote share is decreasing in candidates' identity differentiation even if the posited strategy profile is asymmetric.

to Lindbeck and Weibull (1987), Krasa and Polborn (2010, 2014), Matakos and Xefteris (2016) and Xefteris (2016). Indeed, as all these papers show, candidate differentiation in non-economic issues affects the equilibrium economic policies. All that the current example aimed at illustrating was the simple fact that, an increasing degree of identity differentiation between candidates makes candidates want to pander more to their core constituencies rather than reacting to changes in the general electorates' preferences.

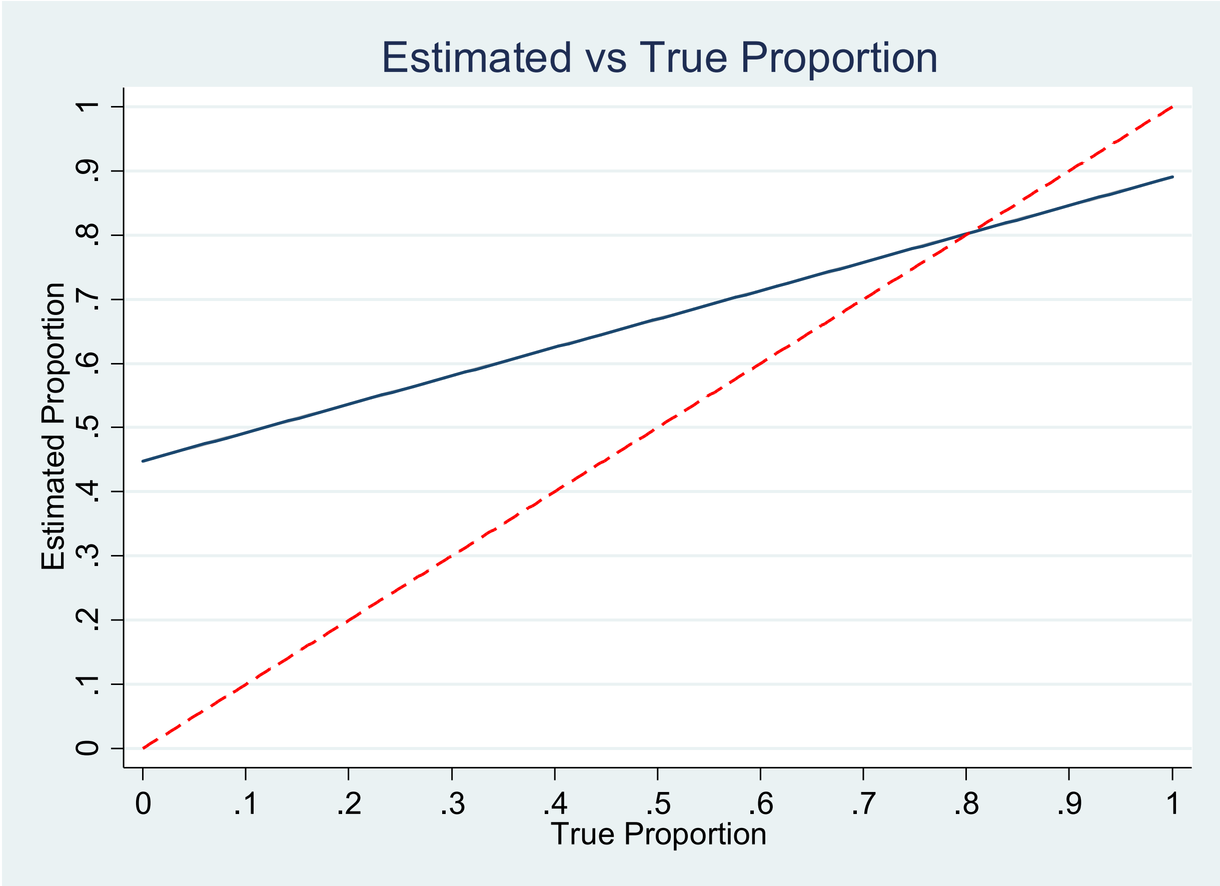


**Fig. A.1:** Estimated and true proportion of white population in randomly selected groups of 50 candidates
*Note:* dashed line represents the 45-degree line.

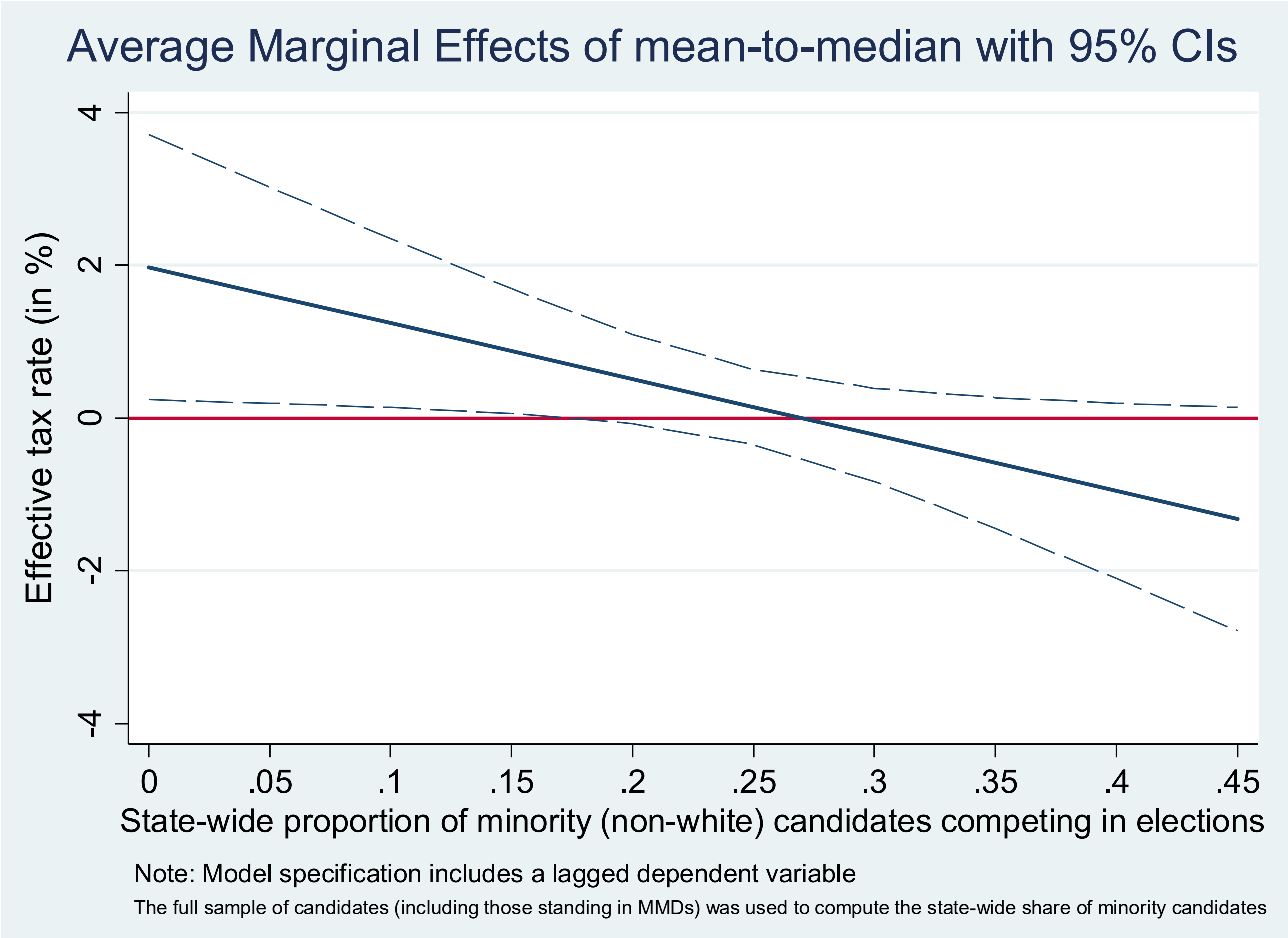


**Fig. A.2** Robustness check: Conditional effects of income inequality (mean-to-median ratio) on the effective tax rate when candidate differentiation is measured by the state-wide proportion of minority (non-white) candidates

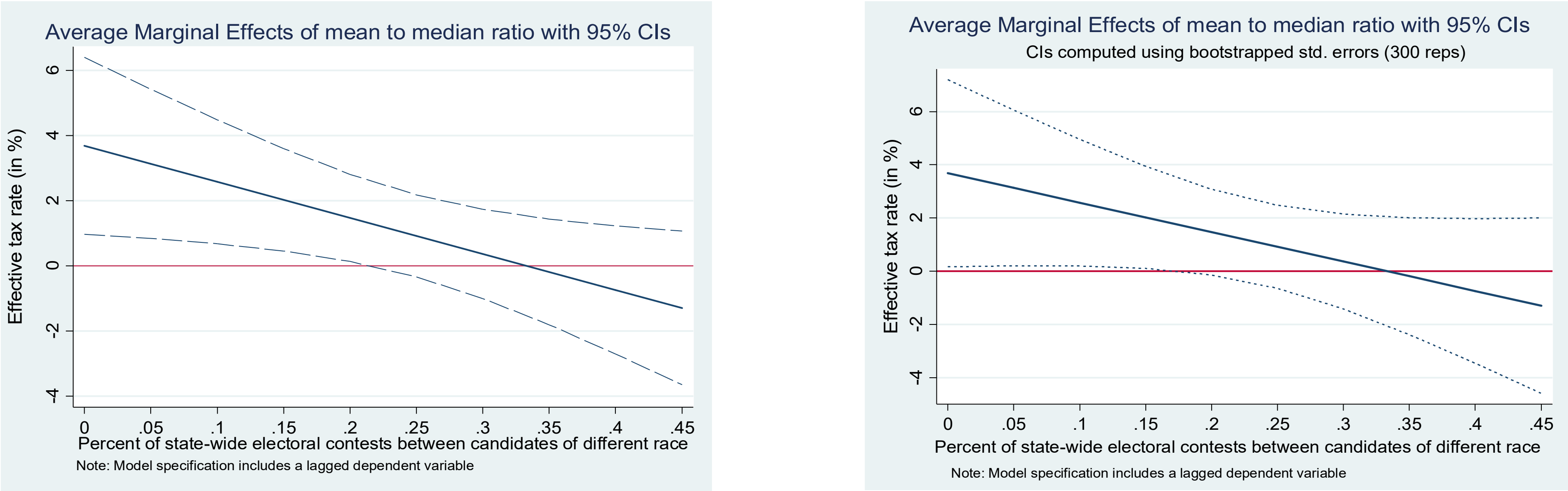


**Fig. A.3** The conditional effect of mean/median ratio on effective State tax rate with clustered (left panel) and bootstrapped (right panel) standard errors.

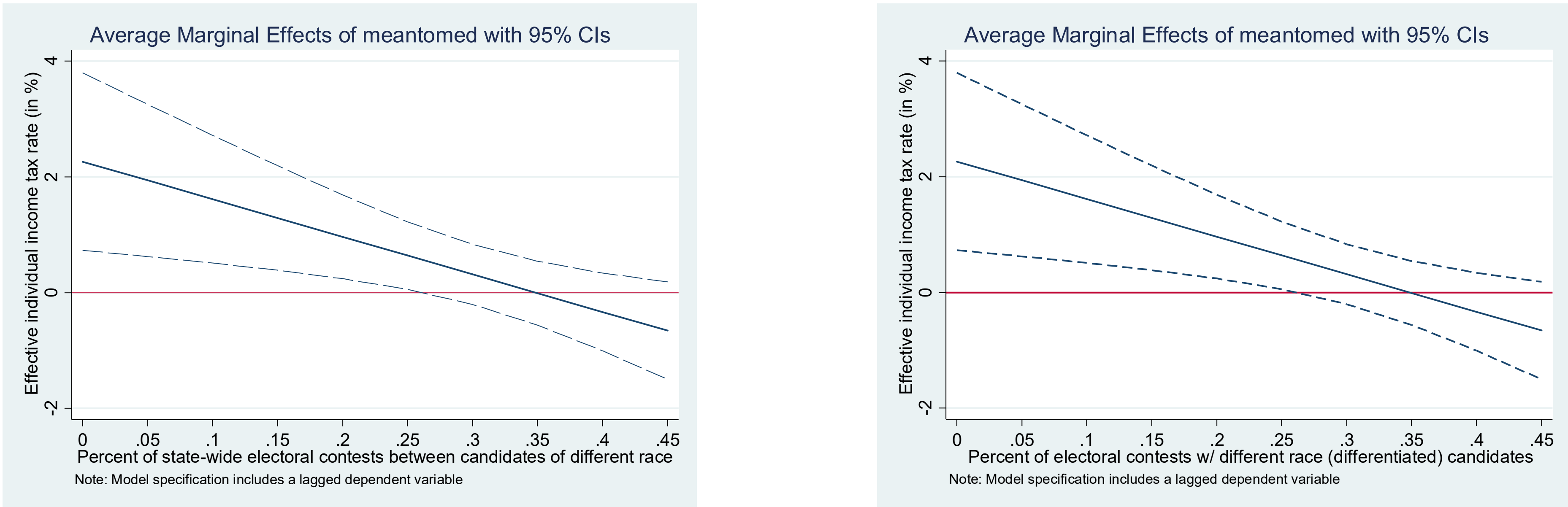


**Fig. A.4** The conditional effect of mean/median ratio on effective individual income State tax rate with clustered (left panel) and bootstrapped (right panel) standard errors.

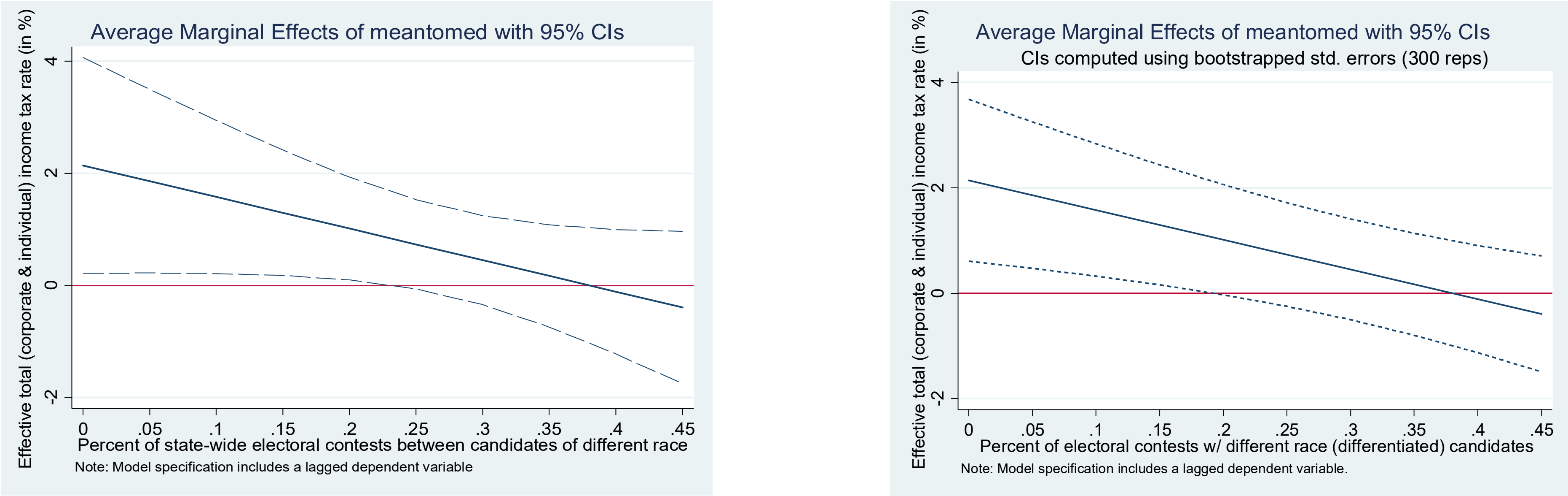


**Fig. A.5** The conditional effect of mean/median ratio on effective total income tax rate with clustered (left panel) and bootstrapped (right panel) standard errors.

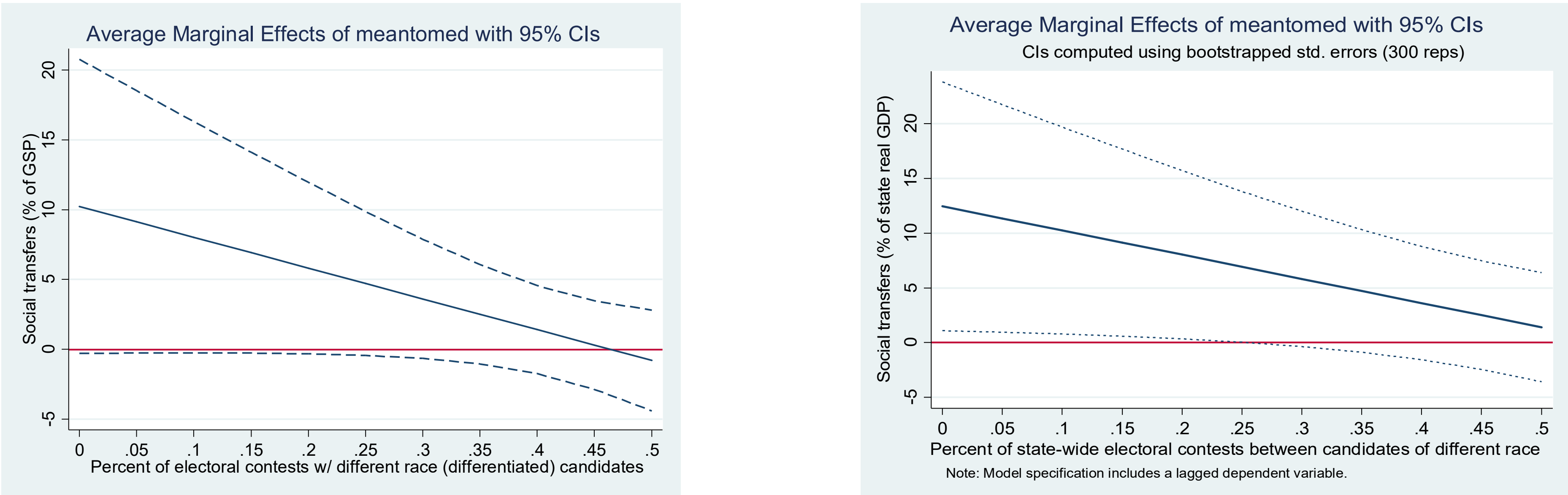


**Fig. A.6** The conditional effect of mean/median ratio on social transfers (as % of state GDP) with clustered (left panel) and bootstrapped (right panel) standard errors.

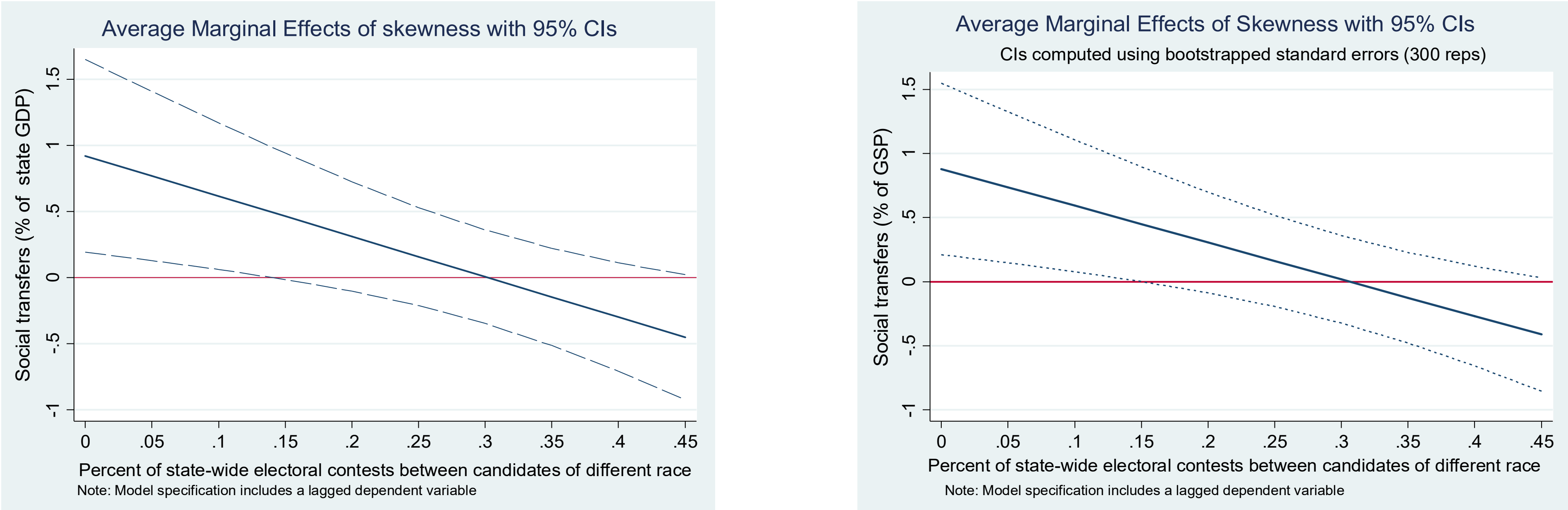


**Fig. A.7** The conditional effect of the skewness of the income distribution on state social transfers with clustered (left panel) and bootstrapped (right panel) standard errors.

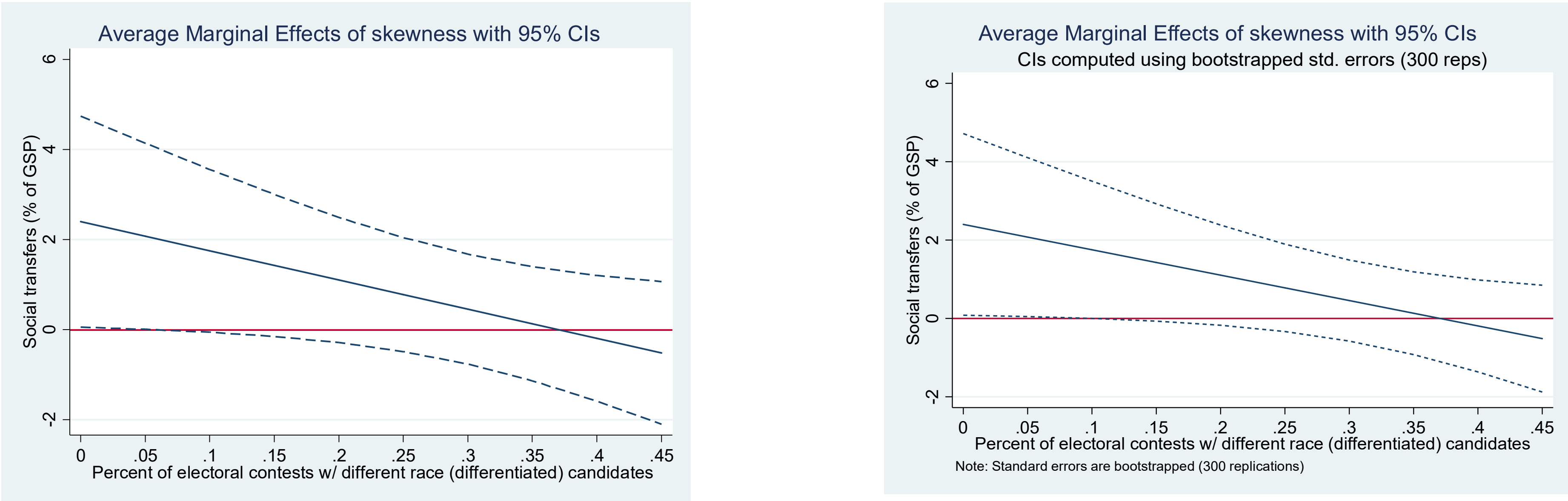


**Fig. A.8** The conditional effect of the skewness of the income distribution on social transfers with clustered (left panel) and bootstrapped (right panel) standard errors.

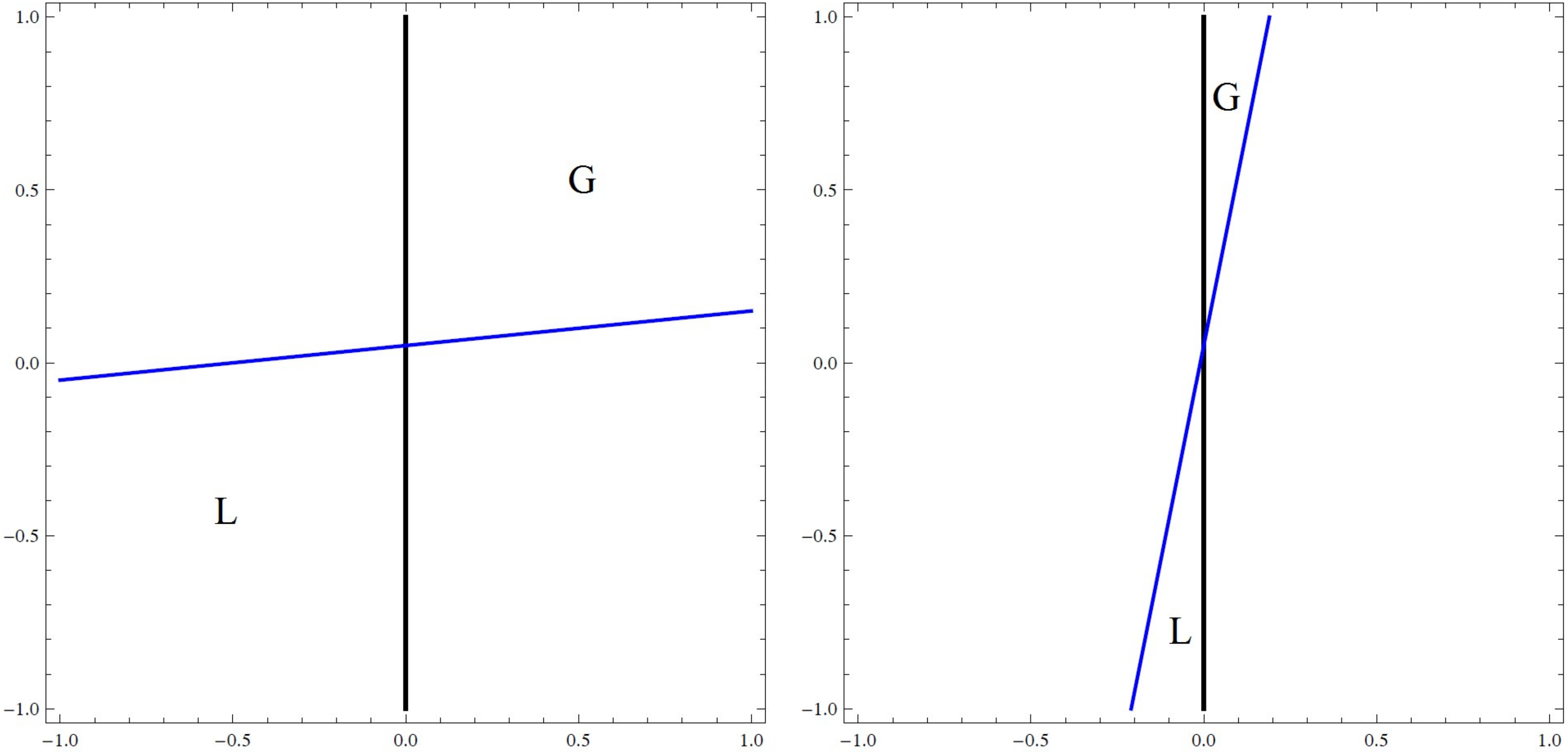


**Figure A.9**. The bliss points of indifferent voters when the first candidate proposes economic platform $a_2 = 0$ (black line) and when she proposes economic platform $a_2 = 0.1$ (blue line), when $a_1 = -b_1 = -0.01$ (left panel) and when $a_1 = -b_1 = -0.5$ (right panel); considering that $b_2 = 0$.

**Table A.1:** The Effects of Inequality and Racial Fragmentation on Redistribution

| **Dependent Variable** | *Effective State Tax Rate* | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | **(1)** | **(2)** | **(3)** | **(4)** | **(5)** | **(6)** | **(7)** | **(8)** | **(9)** |
| *Inequality measures* ($\beta_1$) | | | | | | | | | |
| Mean / Median ratio ($\bar{y}/y^{50}$) | 1.482 | -0.514 | 0.064 | -1.416 | -.- | -.- | -.- | -1.675 | -.- |
| | (3.687) | (2.568) | (3.605) | (2.628) | | | | (2.776) | |
| Skewness | -.- | -.- | -.- | -.- | 0.064 | 0.330 | 0.113 | 0.130 | -.- |
| | | | | | (0.261) | (0.425) | (0.323) | (0.277) | |
| P90 / P10 ratio | -.- | -.- | -.- | -.- | 0.008 | 0.094 | 0.033 | -.- | -.- |
| | | | | | (0.037) | (0.054)* | (0.039) | | |
| P90 / P50 ratio | -.- | -.- | -.- | -.- | -.- | -.- | -.- | -.- | 0.655 |
| | | | | | | | | | (0.733) |
| P50 / P10 ratio | -.- | -.- | -.- | -.- | -.- | -.- | -.- | -.- | 0.015 |
| | | | | | | | | | (0.228) |
| *Ethnic/racial heterogeneity* | | | | | | | | | |
| ERF index ($\beta_2$) | -0.284 | -0.909 | -1.818 | -2.044 | -0.136 | -0.839 | -0.293 | -2.190 | -0.663 |
| | (3.126) | (2.099) | (3.382) | (2.381) | (0.354) | (0.483)* | (0.434) | (2.559) | (0.440) |
| ERF * Inequality ($\beta_3$) | -0.387 | 0.442 | 0.930 | 1.404 | -0.101 | 0.150 | 0.037 | 1.518 | -.- |
| | (2.377) | (1.598) | (2.569) | (1.773) | (0.131) | (0.201) | (0.162) | (1.899) | |
| GOP control | -.- | -.- | -0.318 | -0.210 | -.- | -0.308 | -0.205 | -0.212 | -0.299 |
| | | | (0.169)* | (0.121)* | | (0.166)* | (0.121)* | (0.125)* | (0.156)* |
| Lagged Dep. Var. | NO | YES | NO | YES | YES | NO | YES | YES | NO |
| Other Controls | NO | NO | YES | YES | NO | YES | YES | YES | YES |
| State fixed effects | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Election-year fixed effects | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| $R^2$ | 0.73 | 0.79 | 0.74 | 0.80 | 0.79 | 0.74 | 0.80 | 0.80 | 0.74 |
| *N (obs.)* | 751 | 675 | 735 | 660 | 675 | 735 | 660 | 660 | 735 |

* $p$<0.1; ** $p$<0.05; *** $p$<0.01

*Note*: Robust standard errors clustered at the state level reported in parentheses. The estimation is based on the model of equation 1 but relying only on election (not calendar) years as our unit of analysis. Dependent variable is the effective state tax rate (in %). Inequality measures are the mean-to-median ratio (columns 1-4 and 8), the skewness of the (gross) income distribution (columns 5-8), and the P90/P10, P90/P50 and P50/P10 percentile income ratios. Other controls include: log of real (state) GDP per capita, unemployment rate, female labor force participation rate, growth rate, and a dummy variable indicating whether both chambers of the state's legislature (State House and State Senate) are controlled by the Republican (GOP) party. Columns 3, 4, 6, 7, 8, and 9 have fewer observations due to missing controls for year 1979. Columns 2, 4, 5, 7, 8, and 9 have fewer observations due to the use of a lagged dependent variable in the estimation.

**Table A.2**: The Effect of Inequality on Redistribution (effective state tax rate)

| **Dependent variable** | *Effective State Tax Rate* | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | **(1)** | **(2)** | **(3)** | **(4)** | **(5)** | **(6)** | **(7)** | **(8)** | **(9)** |
| *Measures of Inequality* $(\beta_1)$ | | | | | | | | | |
| Mean / Median ratio $(\bar{y}/y^{50})$ | 0.474<br>(1.120) | 0.196<br>(0.557) | 0.918<br>(1.367) | 0.381<br>(0.688) | -.- | -.- | -.- | 0.296<br>(0.612) | -.- |
| Skewness | -.- | -.- | -.- | -.- | 0.001<br>(0.065) | 0.428<br>(0.303) | 0.122<br>(0.158) | 0.086<br>(0.128) | -.- |
| P90 / P10 ratio | -.- | -.- | -.- | -.- | 0.013<br>(0.015) | 0.066<br>(0.048) | 0.018<br>(0.018) | -.- | -.- |
| P90 / P50 ratio | -.- | -.- | -.- | -.- | -.- | -.- | -.- | -.- | 0.334<br>(0.543) |
| P50 / P10 ratio | -.- | -.- | -.- | -.- | -.- | -.- | -.- | -.- | 0.045<br>(0.144) |
| *Ethnic/Racial heterogeneity* | | | | | | | | | |
| ERF index $(\beta_2)$ | -0.852<br>(0.411)** | -0.247<br>(0.146)* | -0.754<br>(0.382)* | -0.232<br>(0.155) | -0.247<br>(0.138)* | -0.694<br>(0.361)* | -0.213<br>(0.133) | -0.223<br>(0.145) | -0.765<br>(0.399)* |
| GOP control | -.- | -.- | -0.376<br>(0.164)** | -0.174<br>(0.077)** | -.- | -0.368<br>(0.162)** | -0.174<br>(0.077)** | -0.175<br>(0.078)** | -0.370<br>(0.163)** |
| Other controls | NO | NO | YES | YES | NO | YES | YES | YES | YES |
| State and Year FE | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Lagged dep. variable | NO | YES | NO | YES | YES | NO | YES | YES | YES |
| $R^2$ | 0.75 | 0.87 | 0.76 | 0.87 | 0.87 | 0.76 | 0.87 | 0.87 | 0.76 |
| *N (obs.)* | 1,650 | 1,600 | 1,616 | 1,568 | 1,600 | 1,616 | 1,568 | 1,568 | 1,616 |

* $p$<0.1; ** $p$<0.05; *** $p$<0.01

*Note*: Robust standard errors clustered at the state level reported in parentheses. The estimation is based on the model presented in Table A.1 but, this time, relying on calendar (not only election) years. Dependent variable is the effective state tax rate (in %). In all specifications the interaction term between the ERF index and inequality (the term $ERF_{s,t} * Inequality_{s,t}$ in equation 1) is always included in every specification but the coefficient estimate $(\beta_3)$ is not reported in the table. Other controls include: log of real (state) GDP per capita, unemployment rate, female labor force participation rate, growth rate, and a dummy variable indicating whether both chambers of the state's legislature (State House and State Senate) are controlled by the Republican (GOP) party. Columns 3, 4, 6, 7, 8, and 9 have fewer observations due to missing controls for year 1979. Columns 2, 4, 5, 7, 8, and 9 have fewer observations due to the use of a lagged dependent variable in the estimation.

**Table A.3** Robustness check on the mechanism: Non-white president

| **Dependent variable** | (1)<br>Eff. Tax | (2)<br>Eff. Tax |
|---|---|---|
| Non-white President $P_{s,t}$ $(\beta_1)$ | 1.712* | 1.619 |
| | (1.002) | (0.971) |
| Interaction term $P_{s,t}$*Inequality $(\beta_2)$ | -1.461* | -1.368* |
| | (0.805) | (0.774) |
| *Inequality* $(\beta_3)$ | | |
| Mean / Median ratio $(\bar{y}/y^{50})$ | 0.270 | 0.554 |
| | (0.359) | (1.153) |
| *Ethnic/Racial heterogeneity* | | |
| ERF index $(\beta_4)$ | -.- | -0.292 |
| | | (1.088) |
| ERF * Inequality $(\beta_5)$ | -.- | 0.0937 |
| | | (0.830) |
| Observations | 1,600 | 1,600 |
| R-squared | 0.857 | 0.857 |
| Other Controls | YES | YES |
| Lagged dependent variable | YES | YES |
| State and Election-year FE | YES | YES |

* $p$<0.1; ** $p$<0.05; *** $p$<0.01

*Note:* Robust standard errors clustered at the state level reported in parentheses. Dependent variable is the (state) effective tax rate (in %) and social (state) transfers (as % of state GDP) -in column 6. The unit of analysis is the state-election year. One-tailed test p-value = 0.03.

**Table A.4:** The Effect of Inequality and Candidate Differentiation on Redistribution and Social Spending

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| **Dependent Variable:** Eff. Tax | Above 5% | Above 5% | Above 10% | Above 10% | Above 10% | Above 15% | Above 15% | Above 15% |
| *Above 5%* | | | | | | | | |
| Share of heterogeneous contests $P_{s,t}$ ($\beta_1$) | 36.69** | 30.33** | -.- | -.- | -.- | -.- | -.- | -.- |
| | (14.42) | (14.34) | | | | | | |
| Interaction term $P_{s,t}$ * *Inequality* ($\beta_2$) | -28.77** | -24.34** | -.- | -.- | -.- | -.- | -.- | -.- |
| | (11.79) | (11.97) | | | | | | |
| *Ethnic/Racial heterogeneity* | | | | | | | | |
| ERF index ($\beta_3$) | -10.72** | -10.19** | -10.29** | -9.689* | -4.232* | -10.34** | -9.622* | -4.269* |
| | (4.987) | (4.951) | (4.997) | (4.990) | (2.133) | (5.006) | (4.939) | (2.130) |
| *Inequality* ($\beta_4$) | | | | | | | | |
| Mean / Median ratio ($\bar{y}/y^{50}$) | -5.056 | -4.982 | -4.799 | -4.694 | -2.499 | -4.886 | -4.723 | -2.563 |
| | (4.059) | (4.216) | (4.076) | (4.236) | (1.927) | (4.074) | (4.205) | (1.905) |
| ERF * *Inequality* ($\beta_4$) | 8.119** | 7.768* | 7.768* | 7.358* | 3.377* | 7.801* | 7.291* | 3.398* |
| | (3.960) | (4.005) | (3.967) | (4.039) | (1.744) | (3.960) | (3.991) | (1.735) |
| GOP controls legislature | -.- | -0.303* | -.- | -0.302* | -0.152 | -.- | -0.300* | -0.150 |
| | | (0.160) | | (0.160) | (0.098) | | (0.159) | (0.0970) |
| *Above 10%* | | | | | | | | |
| Share of heterogeneous contests $P_{s,t}$ ($\beta_1$) | -.- | -.- | 35.37** | 28.70* | 12.38** | -.- | -.- | -.- |
| | | | (14.38) | (14.49) | (6.013) | | | |
| Interaction term $P_{s,t}$ * *Inequality* ($\beta_2$) | -.- | -.- | -27.68** | -22.97* | -9.785* | -.- | -.- | -.- |
| | | | (11.74) | (12.11) | (5.046) | | | |
| *Above 15%* | -.- | -.- | -.- | -.- | -.- | 35.51** | 28.45* | 12.49** |
| Share of heterogeneous contests $P_{s,t}$ ($\beta_1$) | | | | | | (14.21) | (14.25) | (5.867) |
| Interaction term $P_{s,t}$ * *Inequality* ($\beta_2$) | -.- | -.- | -.- | -.- | -.- | -27.63** | -22.57* | -9.729* |
| | | | | | | (11.57) | (11.93) | (4.958) |
| Observations | 751 | 735 | 751 | 735 | 732 | 751 | 735 | 732 |
| R-squared | 0.732 | 0.740 | 0.732 | 0.740 | 0.852 | 0.732 | 0.740 | 0.852 |
| Other Controls | NO | YES | NO | YES | YES | NO | YES | YES |
| Lagged dependent variable | YES | YES | YES | YES | YES | YES | YES | YES |
| State and Election-year FE | YES | YES | YES | YES | YES | YES | YES | YES |

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

*Note*: Robust standard errors clustered at the state level reported in parentheses. Dependent variable is the (state) effective individual and total (individual plus corporate) income and tax rate (in %) and social (state) transfers (as % of state GDP). Data for social transfers are available from 1997 and onwards. LI inequality stands for low income inequality across racial groups and HI inequality stands for high-income inequality across racial groups. Other controls include: log of real (state) GDP per capita, unemployment rate, female labor force participation rate, growth rate, and a dummy variable indicating whether both chambers of the state's legislature (State House and State Senate) are controlled by the Republican (GOP) party.

**Table A.5:** The Effect of Inequality and Candidate Differentiation on Redistribution (only winners)

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Dependent variable: Eff. Tax | Only winners | Only winners | Only winners | Only winners |
| *Candidate differentiation* | | | | |
| Share of heterogeneous contests-only winners $P_{s,t}$ ($\beta_1$) | 32.27** | 14.00** | | |
| | (14.15) | (6.301) | | |
| Interaction term $P_{s,t}$* *Inequality* ($\beta_2$) | -26.14** | -11.20** | | |
| | (11.75) | (5.212) | | |
| State-wide share of non-white (minority) winners $P_{s,t}$ ($\beta_1$) | | | 12.64* | 4.335 |
| | | | (7.331) | (3.534) |
| Interaction term $P_{s,t}$* *Inequality* ($\beta_2$) | | | -10.96** | -3.257 |
| | | | (5.699) | (2.858) |
| *Ethnic/racial heterogeneity* | | | | |
| ERF index ($\beta_4$) | -10.74** | -4.706** | 1.969 | 0.274 |
| | (4.987) | (2.299) | (4.071) | (1.461) |
| *Inequality* ($\beta_3$) | | | | |
| Mean / Median ratio ($\bar{y}/y^{50}$) | -5.260 | -2.761 | 14.06* | 3.757 |
| | (4.240) | (2.026) | (7.941) | (3.748) |
| ERF * Inequality ($\beta_5$) | 8.239** | 3.773** | -2.281 | -0.290 |
| | (4.028) | (1.870) | (3.125) | (1.169) |
| GOP controls legislature | -0.307* | -0.154 | -0.297* | -0.163 |
| | (0.161) | (0.0991) | (0.168) | (0.106) |
| Observations | 735 | 732 | 735 | 732 |
| R-squared | 0.740 | 0.852 | 0.739 | 0.852 |
| Other Controls | YES | YES | YES | YES |
| Lagged dependent variable | YES | YES | YES | YES |
| State and Election-year FE | YES | YES | YES | YES |

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

*Note*: Robust standard errors clustered at the state level reported in parentheses. Dependent variable is the (state) effective individual and total (individual plus corporate) income and tax rate (in %) and social (state) transfers (as % of state GDP). Other controls include: log of real (state) GDP per capita, unemployment rate, female labor force participation rate, growth rate, and a dummy variable indicating whether both chambers of the state's legislature (State House and State Senate) are controlled by the Republican (GOP) party.

**Table A.6:** The Effect of Inequality and Candidate Differentiation on Redistribution

| **Dependent Variable** | *Eff. Tax* | *Eff. Tax* | *Eff. Tax* | *Eff. Tax* | *Eff. Tax* | *Transfers* |
|---|---|---|---|---|---|---|
| | **(1)** | **(2)** | **(3)** | **(4)** | **(5)** | **(6)** |
| *Candidate differentiation* | | | | | | |
| Share of heterogeneous contests $P_{s,t}$ ($\beta_1$) | 38.027 | 16.195 | 13.840 | 32.098 | 4.730 | 5.308 |
| | (16.892)** | (12.548) | (8.082)* | (13.538)** | (1.391)*** | (2.035)*** |
| Interaction term $P_{s,t}$ * Inequality ($\beta_2$) | -29.944 | -12.542 | -11.055 | -25.891 | -4.370 | -2.870 |
| | (13.982)** | (10.704) | (6.879)* | (11.563)** | (1.750)** | (0.971)*** |
| *Measures of Inequality* ($\beta_3$) | | | | | | |
| Mean / Median ratio ($\bar{y}/y^{50}$) | -5.259 | -2.679 | -2.729 | -5.242 | -.- | -.- |
| | (2.746)* | (1.800) | (1.926) | (2.769)* | | |
| Theil index | -.- | -.- | -.- | -.- | -2.464 | -.- |
| | | | | | (0.976)** | |
| Skewness | -.- | -.- | -.- | -.- | -.- | -0.655 |
| | | | | | | (0.369)* |
| *Ethnic/Racial heterogeneity* | | | | | | |
| ERF index ($\beta_4$) | -11.101 | -4.708 | -4.660 | -10.687 | -1.821 | -1.219 |
| | (4.332)** | (2.506)* | (1.962)** | (3.996)*** | (0.614)*** | (0.557)** |
| ERF * Inequality ($\beta_5$) | 8.439 | 3.769 | 3.732 | 8.185 | 1.561 | 0.813 |
| | (3.552)** | (2.100)* | (1.630)** | (3.240)** | (0.522)*** | (0.275)*** |
| GOP controls legislature | -.- | -.- | -0.153 | -0.304 | -0.294 | -0.014 |
| | | | (0.071)** | (0.101)*** | (0.102)*** | (0.077) |
| Other controls | NO | NO | YES | YES | YES | YES |
| Lagged dependent variable | NO | YES | YES | NO | YES | YES |
| State and Election-year FE? | YES | YES | YES | YES | YES | YES |
| $R^2$ | 0.73 | 0.85 | 0.85 | 0.74 | 0.74 | 0.99 |
| *N (obs.)* | 751 | 748 | 735 | 735 | 735 | 321 |

* $p$<0.1; ** $p$<0.05; *** $p$<0.01

*Note:* Bootstrapped standard errors (300 repetitions) reported in parentheses. Dependent variable is the (state) effective tax rate (in %) and social (state) transfers (as % of state GDP) -in column 7. Reported estimates are based on the specification presented in equation 2 (Table 2). Other controls include: log of real (state) GDP per capita, unemployment rate, female labor force participation rate, growth rate, and a dummy variable indicating whether both chambers of the state's legislature (State House and State Senate) are controlled by the Republican (GOP) party. The unit of analysis is the state-election year. Columns 2 to 6 have fewer observations due to some missing controls in year 1980. Column 7 has fewer observations because data on social transfers at the state level are available after 1997.