The Impact of Party Affiliation of U.S. Governors on Immigrants' Labor-Market Outcomes*

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Abstract

Do immigrants have better labor-market outcomes under Democratic governors? By exploiting variations associated with close elections in a regression discontinuity (RD) design applied on gubernatorial elections in 50 states over the last two decades, we find that immigrants are more likely to be employed, work longer hours and more weeks, and have higher earnings under Democratic governors. We present evidence that Democratic governors implement policies which create better labor-market conditions in certain occupations where immigrants are concentrated. Our findings are robust to a number of different specifications, controls, and samples.

JEL Classification: J15, J21, J31, D72
Keywords: Earning Gaps, Immigration, Labor-market Outcomes, Political Parties, Regression Discontinuity

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1 Introduction

Immigrants are significantly changing the racial composition of America. For instance, the share of U.S. population that is foreign-born rose steadily from 5 percent in 1970 to 15 percent in 2010, and today there are more Latinos than African Americans (CBO, 2013). This profound change in U.S. population has major political consequences as well, because immigrants are more Democratic in their party identification and voting preferences (Petrocik, 2009).

In this paper, we investigate whether immigrants are better off under Democratic rule. Specifically, we estimate the causal impact of the party affiliations of U.S. governors on immigrants' labor-market outcomes. Using more than 250 gubernatorial elections in 50 states between 1993 and 2013, we address the problem by exploiting random variation associated with close elections in a regression discontinuity (RD) design. Labor-market outcomes are measured by employment status, usual hours worked per week, weeks worked per year, total annual hours, and hourly, weekly, and annual incomes. We find that Democratic governors do not have any impact on white natives, but they have positive and significant impact on immigrants' labor-market outcomes. For example, immigrants (relative to white natives) have a 1.5 percent higher employment rate, and increase their total annual working hours and annual income by 1.8 and 4.2 percent, respectively, under Democratic governors.

Why are immigrants better off under Democratic governors? Several studies have shown that Democrats tend to raise taxes, spend more (on education, health, and infrastructure), increase minimum wages, support labor unions (e.g., Besley and Case, 2003; Reed, 2006; Leigh, 2008; Beland and Oloomi, 2015; Dark, 2001). Consequently, the main explanation for the above causal impact of the Democratic governors on immigrants may stem from the policies implemented by Democrats that created better job opportunities and conditions in certain occupations and sectors where immigrants are more concentrated. We provide evidence that supports this explanation.

In our sample, the majority of immigrant workers (about 55%) have high school or less education, and about two-thirds of them are construction workers, repair workers, food preparation and serving workers, personal and health care practitioners, teachers, and assemblers and operators. Our analysis shows that restricting the sample to these occupations and controlling for differences in state-level minimum wage, per capita government spending on education, health, and infrastructure, unionization rates, state earned income tax credit (EITC) reduces the impact of Democratic governors on immigrants' labor-market outcomes more than 50 percent. In addition, we find that party affiliation has almost no impact on immigrants' labor markets when the sample is restricted to remaining occupations such as managers and CEOs, architects and engineers, business and financial practitioners, etc.

We also conduct an extensive sensitivity analysis to investigate the robustness of our approach and findings. A particularly important part of our sensitivity analysis is about the validity of the RD design for our analysis.[1] Following Lee and Lemieux's (2014) recommended checklist for implementation of RD designs, we present statistical evidences that strongly support the validity of our approach in the present context. We also show that the main results are robust to using different samples, conditioning variables, and specifications.

This paper constructs a new link between immigration and political economy literatures. The literature on immigration has mainly investigated how immigration has affected different aspects of economies such as labor markets (Hunt and Friedberg, 1999; Borjas, 2003; Card, 2001 and 2009; Ottaviano and Peri, 2012), investment in human capital (McHenry, 2015), productivity (Peri, 2012), innovation and technological choice (Hunt, 2010; Lewis, 2011; Peri, 2012), and prices (Cortes, 2008). Another strand of the literature investigates the welfare implications of immigration, in particular, its effect on public finances (Alesina et al., 1999; Razin et al., 2002; Preston, 2013). Our contribution

[1] Using RD designs to estimate program effects in a variety of contexts have become quite popular in economics. Lee and Lemieux (2010 and 2014) provide a comprehensive review of the literature by discussing identification, interpretation, and estimation issues related to RD designs.

to this literature is to uncover the impact of the political environment on immigrants' labor-market outcomes.

This paper also relates to the political economy literature that investigates the impact of political representation on policy outcomes. U.S. elected officials have high degree of autonomy to exercise their power in their voting behavior and policy choices, recent studies have documented that the party affiliation has a significant impact on their actions.[2] In an influential paper, Lee et al. (2004), using a RD design, find that the party affiliation has a large impact on a legislator's voting behavior.[3] Recent papers find that partisan affiliation of governors matter for policy outcomes. Besley and Case (2003), using a fixed effect regression analysis for the time period 1950-1998, estimate the impact of the party affiliation of governors on state taxes and expenditures (see also Beland and Oloomi, 2015). They find that Democratic governors and a higher proportion of seats held by Democrats in the state upper and lower houses is associated with higher state taxes and spending per capita. In a related paper, Reed (2006) shows that tax burdens are higher when Democrats control the governor office and state legislature.

Our paper is related to Beland (2015) who investigates the effect of the party affiliation of U.S. governors on black workers' labor-market outcomes. Employing a RD design on gubernatorial elections between 1977 and 2008, he finds that Democratic governors increase the annual hours worked by blacks relative to whites, which in turn reduces the earnings gap between the two groups. Furthermore, he finds that Democratic governors have a positive impact on employment rates of blacks relative to whites. Our paper differs from his by focusing on the impact of governors' party affiliations on the labor-market

[2]The literature on this subject is vast. Important contributions are Garand (1988), Besley and Case (1995), Knight (2000), Alt and Lowry (2000) among many others. Besley and Case (2003) provides an early review of the literature.

[3]Ferreira and Gyourko (2009) investigate whether cities are as politically polarized as states. Exploiting the random variation associated with close U.S. municipal elections between 1950 and 2000, they find that whether the mayor is a Democrat or Republican has an insignificant impact on the size of local government, the composition of local public expenditure, or crime rate. Our paper, methodologically, is closely related to their work. Employing an RD design on panel data from Swedish local governments, Pettersson-Lidbom (2008) finds that left-wing governments spend and tax 2-3 percent more than right-wing government.

outcomes of immigrant workers. One interesting finding in our paper is that introducing immigrants into the analysis does not crowd-out the positive impact of Democratic governors on labor inputs of blacks relative to whites.

The plan of this paper is as follows. Section 2 describes the data used in the paper and provides summary statistics related to the main features of the data. Section 3 introduces the econometric specification used in our RD design. Benchmark results and the possible channels through which party affiliation can affect labor-market outcomes are also discussed in this section. The robustness of the benchmark results is discussed in Section 4; and Section 5 offers some concluding remarks.

2 Data Description

The sources of our labor market data are the March Current Population Survey (CPS) files from Integrated Public Use Micro Samples (IPUMS) (2010) for years 1994 to 2014. The time period is dictated by the availability of the data on immigrants. We consider all people between 18 and 64 years old; and for each person, we record the following characteristics: gender, age, race, marital status, immigration status, citizenship status, education level, employment status, industry, occupation, usual hours worked per week, weeks worked last year, labor income earned last year, and the CPS sampling weights. We classified all foreign-born individuals as immigrants (regardless of their citizenship status).[4] In addition, we grouped individuals under three races: white, black, and others.

Income variables are deflated using personal consumption expenditure (PCE) index from the Bureau of Economic Analysis (2014) and are measured in 2009-chained prices.[5]

[4] Thus, those who are born in the U.S. are not considered as immigrant. In addition, our sample exclude all illegal immigrants.

[5] Top-coded incomes for years 1980, 1990, 1994, and 1995 are multiplied by 1.5; but no correction made for the subsequent years. This is because, starting in 1996, top-coded income values are assigned the mean of all top-coded earners, and these numbers are substantially higher than top-coded income values reported in the previous years. The analysis without top-coded earners yields mostly the same results. Following Autor et al. 2008, workers with income below $3.35 per hour (in 2009 dollars) are dropped. In addition, to prevent measurement errors related to hours and weeks reported, in each year, the maximum hourly income of workers is limited to the top-coded annual income divided by 2000 (hours per year). In

Table 1. Summary Statistics on Labor Market Outcomes, 1993–2013

Outcome	Immigrants I	Whites II	Blacks III	Others IV
Unemployment (%)	6.9	5.1	11.1	8.7
	(0.3)	(0.2)	(0.3)	(0.3)
Hours per Week	38.0	39.1	36.7	37.2
	(13.4)	(13.1)	(13.5)	(14.3)
Total Weeks	45.5	46.9	44.0	44.4
	(14.4)	(12.4)	(16.0)	(15.3)
Total Hours	1942	1980	1893	1888
	(632)	(666)	(635)	(701)
Hourly Income	19.6	22.4	17.4	21.0
	(21.8)	(22.1)	(16.4)	(21.91)
Weekly Income	812	950	707	870
	(957)	(1003)	(678)	(936)
Annual Income	38,958	45,815	33,422	40,769
	(47,827)	(50,656)	(33,905)	(46,192)

Notes: The statistics draws on the March CPS samples over 1994–2014. Columns II, III, and IV exclude all immigrants. All calculations are based on the CPS weights.

After cleaning and correcting, the final sample has about 1.6 million observations over the survey years 1994–2014 (i.e., 1993–2013). About 82% of individuals are white, 10% black, and 8% other race. Immigrants make around 15% of our sample, and 60% of them are citizen.

Table 1 presents descriptive statistics about key labor market outcomes across different groups. Numbers in parentheses are the standard deviations. Note that the unemployment rate is higher among immigrants compared to native whites. In addition, although immigrants' labor inputs (measured by hours worked per week, total weeks, and total hours) are very similar to whites, their corresponding income figures are markedly lower than those of white workers.

The winner's party and the margin of victory variables are constructed using the data on gubernatorial elections from the *Atlas of U.S. Presidential Elections* (Leip, 2015). The

this way, we also prevent part-time workers from having a higher feasible wage than full-time, full-year workers (see Autor et al., 2008). Our results are not sensitive to such corrections.

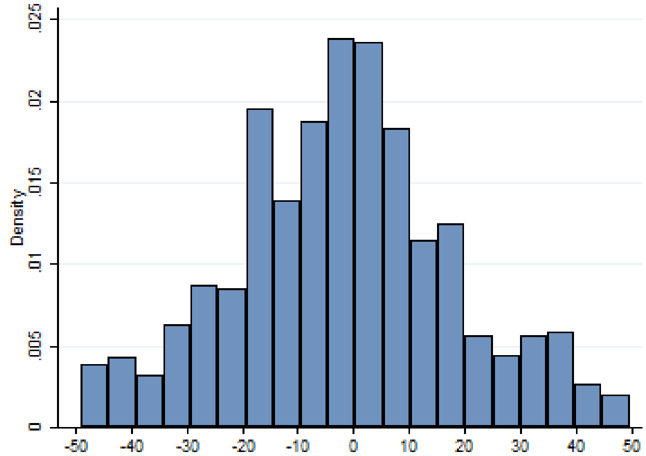


Figure 1. Distribution of the Margin of Victory

data are available for the years 1990 and onward; and for elections prior to 1990, the election outcomes from the ICPSR 7757 (1995) files are used. We only consider elections where a Democrat or a Republican won. From 1993 to 2013, there are 1031 state×year observations. Democrats governed 469 times, which is about 45% of the time.

Figure 1 shows the distribution of the margin of victory (MV) for Democrats across all elections in our sample. The margin of victory is defined as the proportion of votes cast for the winner minus the proportion of votes cast for the candidate who finished second. Observe that the distribution is clustered around the cutoff point with no unusual jumps around it. In addition, the distribution does not show any skewness towards either party. These observations suggest that candidates did not have any influence on the election results, which is an important assumption for the validity of the RD design.[6]

3 Empirical Implementation

3.1 Econometric Specification

To determine the impact of party affiliation of U.S. governors on immigrants' labor market outcomes, we use a Regression Discontinuity (RD) design. To obtain an unbiased estimate

[6]We later formally test this assumption using McCrary's (2008) test.

of the party effect, one needs to address the endogeneity problem arising from factors such as voter characteristics, party incumbency, labor-market conditions, and so on. These factors can influence who wins the election which would bias estimates of the impact of the party allegiance of governors. Following Lee (2008), this identification problem is solved by exploiting the random variations associated with close U.S. gubernatorial elections.

For any labor market outcome, Y, we estimate the following equation:

$$\begin{aligned} Y_{ist} = &\beta_o + \beta_s + \beta_t + \beta_D D_{st} + \beta_{DI} D_{st} \times Img_{ist} + \beta_{DR} D_{st} \times R_{ist} + \beta_I Img_{ist} + \\ &\beta_R R_{ist} + F(MV_{st}) + F_I(MV_{st}) \times Img_{ist} + F_R(MV_{st}) \times R_{ist} + \beta_Z Z_{ist} + \varepsilon_{ist}, \end{aligned} \tag{1}$$

where β_s and β_t denote state and time fixed effects, respectively. In specification (1), D_{st} is an indicator variable that equals one if a Democratic governor is in power in state s in year t, and Img_{ist} is a dummy variable that takes on a value one if the individual is an immigrant. $R_{ist} = [Black_{ist} \quad Other_{ist}]$ is a vector of variables that characterizes each individual's race: *Black* equals one if the individual is black, and *Other* equals one if she is neither white nor black. The variable MV_{st} denotes the marginal victory in the most recent gubernatorial election prior to year t in state s, and $F_j(MV)$ represents a quadratic polynomial function of the variable MV. The margin of victory (MV) is defined as the proportion of votes cast for the winner minus the proportion of votes cast for the candidate who finished second. The cutoff point for the MV is 0 percent, and in our analysis a positive MV indicates that a Democratic governor won, whereas a negative MV indicates that a Republican won.[7] The variable Z is a vector of variables that control individual characteristics such as gender, age, education level, marital status; and finally, ε_{ist} is the error term and we use cps sampling weights.

[7] For Texas, for example, 2006 election results (the political party of the winner and the margin of victory) are used in regressions for 2007, 2008, 2009 and 2010. We exclude observations where neither a Democrat nor a Republican won. Following Gelman and Imbens (2014), we assume that $F_j(MV)$ is a second-order polynomial function. However, considering first- or third-order polynomials yields very similar results. Results are also similar using local linear regression discontinuity (see Section 4).

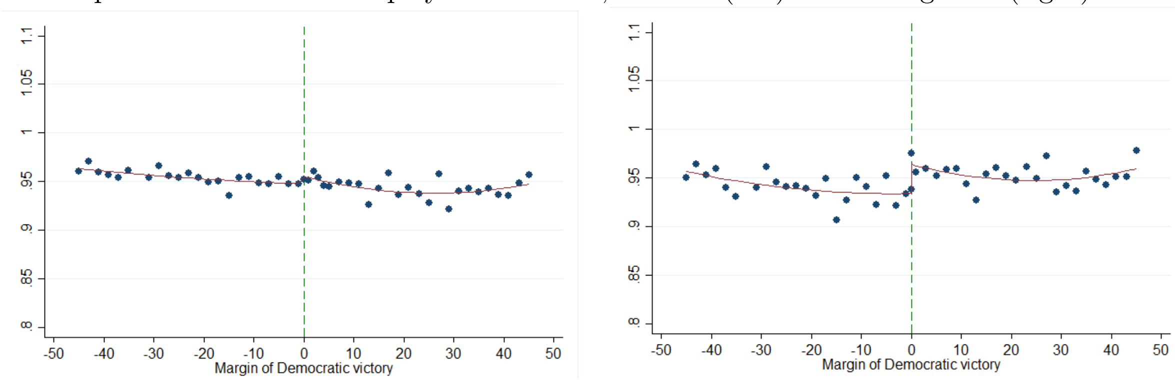
The coefficients of interest are β_D, β_{DI}, and β_{DR}. Note that since $R = [Black \quad Other]$, the coefficient β_D measures the impact of a Democratic governor on white, native workers. According to equation (1), party affiliation effects (i.e., β_D, β_{DI}, β_{DR}) are estimated controlling for the variations in the MV (presented by second-order polynomial functions) as well as other individual and state characteristics. We use the following labor-market outcomes in estimating equation (1): employment status (i.e., employed or not), usual hours worked per week, total weeks worked per year, total annual hours, hourly income, weekly income, and annual income. All variables except for employment status are in logs and are conditional on working. Standard errors are clustered at the state level which enables accounting for potential serial correlation.

3.2 Graphical Evidence

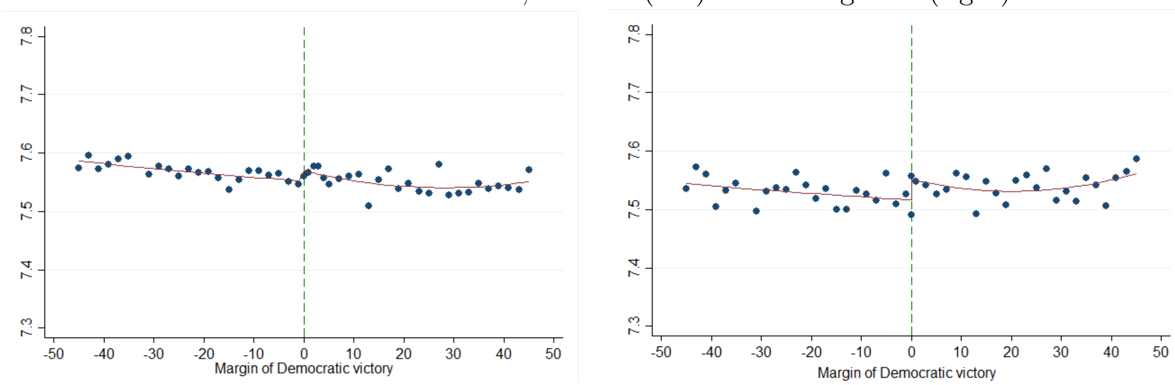
As is customary in the RD analysis, we first present some graphic evidence on the impact of Democratic governors on immigrants' labor market outcomes. Figures 2.a, 2.b, and 2.c explore the implications of the discontinuity at 0% when a Democratic governor barely wins over a Republican. In each panel, the graph on the left represents white, native workers; and the one on the right represents immigrants. Figure 2.a presents the proportion of workers employed; Figure 2.b presents the total hours worked; and Figure 2.c shows the annual earnings for each group.

In each graph, each dot represents the average outcome that follows election t, grouped by margin of victory intervals. The solid curves in the figures represent the predicted values from the quadratic polynomial fit without covariates. Figures 2.a suggests that the proportion of immigrants who are employed under Democratic governors is higher, and Figure 2.b indicates that they work more hours. According to Figure 2.c, immigrants earn more under Democratic governors.

a. Proportion of Workers Employed for White, Natives (left) and Immigrants (right)



b. Total Hours Worked for White, Natives (left) and Immigrants (right)



c. Annual Earnings for White, Natives (left) and Immigrants (right)

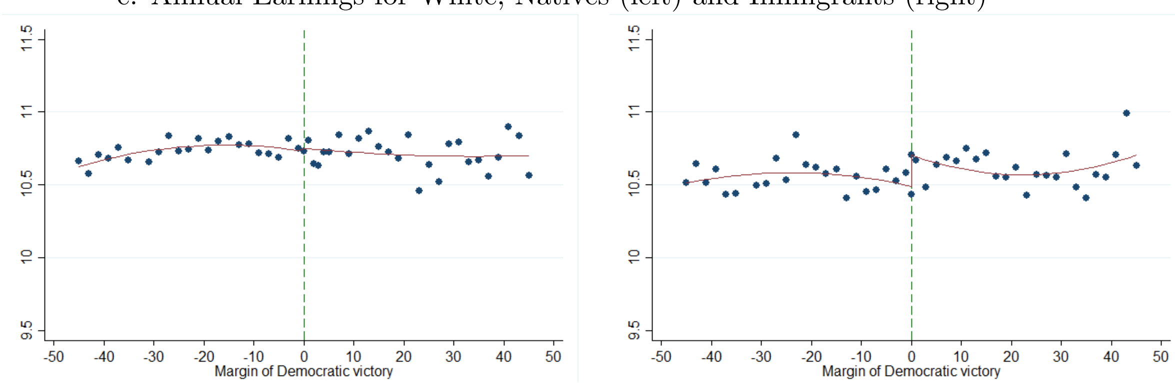


Figure 2: The Impact of Democratic Governors on Labor-market Outcomes

Notes: In each panel, the graph on the left represents white, native workers, and the graph on the right immigrant workers.

3.3 Benchmark Results

Table 2 reports the results based on econometric specification (1). We only report the estimates on the coefficients of interest. Column I represents the impact of Democratic governors on being employed based on standard covariates. The interaction term Img×Dem measures the effect of Democratic governors on the propensity to work for immigrants relative to natives. According to column I, immigrants are more likely to be employed under a Democratic governor: the estimated coefficient is about 1.5 percent and is statistically significant at the 1% level. Similar pattern are observed for black and other races: the corresponding estimates are about 1.9 and 1.2 percents, and are statistically significant at the 1% and 5% level, respectively. The coefficient for natives (captured by the variable Dem) is almost zero (0.2 percent) and is statistically insignificant.

Column II presents the impact of Democratic governors on usual hours worked per week based on standard covariates. The estimated coefficients on the interaction terms are small, positive, and statistically insignificant. As in column I, the coefficient for natives is small (0.4 percent) and statistically insignificant. Consequently, the impact of Democratic governors on usual hours worked per week by any group is insignificant. This conclusion is not surprising because usual hours worked per week are more job specific and less flexible.

Column III reports the results where the labor market outcome is total weeks worked per year. The estimated coefficient on Img×Dem is about 1.7 percent and is statistically significant at the 1% level; and thus, Democratic governors has a positive effect on total weeks worked by immigrants. Similar to column I, the estimated coefficients on Black×Dem and Other×Dem are also positive (2.8 and 1.9 percents, respectively) and statistically significant. The impact of Democratic governors on white natives is positive, small, and statistically insignificant.

Column IV reports the effect of Democratic governors on total annual hours worked, conditional on working. The estimated coefficients are consistent with findings in columns

Table 2. IMPACT OF PARTY AFFILIATION ON LABOR MARKETS OVER 1993–2013

Variable	Emp Status I	Hours per Week II	Total Weeks III	Total Hours IV	Hourly Income V	Weekly Income VI	Annual Income VII
Dem	0.0019	0.0039	0.0020	0.0058	0.0019	0.0063	0.0069
	(0.0020)	(0.0026)	(0.0020)	(0.0040)	(0.0058)	(0.0066)	(0.0064)
Img×Dem	0.0148***	0.0013	0.0171***	0.0183**	0.0408***	0.0390***	0.0417***
	(0.0035)	(0.0052)	(0.0048)	(0.0082)	(0.0120)	(0.0125)	(0.0126)
Black×Dem	0.0190***	0.0017	0.0283***	0.0300***	0.0334**	0.0318**	0.0345**
	(0.0032)	(0.0056)	(0.0055)	(0.0094)	(0.0125)	(0.0140)	(0.0145)
Other×Dem	0.0116**	0.0055	0.0187***	0.0242***	0.0151	0.0148	0.0162
	(0.0049)	(0.0050)	(0.0065)	(0.0087)	(0.0134)	(0.0147)	(0.0151)
Img	0.0044	−0.0059	−0.0019	−0.0078	−0.2000***	−0.2086***	−0.2058***
	(0.0034)	(0.0050)	(0.0024)	(0.0061)	(0.0187)	(0.0197)	(0.0191)
Black	−0.0417***	0.0048	−0.0296***	−0.0249***	−0.0547***	−0.0540***	−0.0582***
	(0.0022)	(0.0031)	(0.0040)	(0.0056)	(0.0151)	(0.0157)	(0.0155)
Other	−0.0075*	−0.0035*	−0.0132**	−0.0167**	−0.0833***	−0.0753***	−0.0704***
	(0.0040)	(0.0019)	(0.0063)	(0.0073)	(0.0217)	(0.0247)	(0.0246)

Notes: All dependent variables but "Emp Status" are in logs. The data draws on the CPS March samples from IPUMS for the survey years 1994–2014. All regressions include state fixed effects, time effects, and all other control variables specified in equation (1). Numbers in parentheses are standard errors based on clustering data at state level; ***, **, and * represent statistical significance at the 1%, 5%, and 10% level, respectively.

II and III (coefficient for Img×Dem is 1.8 percents and statistically significant at 5 percents). In sum, the results presented in columns I–IV indicate that Democratic governors have positive and statistically significant impacts on immigrants' labor inputs.

The last three columns present results based on income figures. According to column V, where the dependent variable is hourly income, the estimated coefficient on Img is -20% and is highly significant; i.e., immigrants are earning significantly lower than any other group, as found in the literature. However, the coefficient on the interaction term Img×Dem is about 4.1 percent and is statistically significant at the 1% level; as a result, Democratic governors have a positive and significant impact on hourly income of immigrants. Note that according to column II, usual hours worked per week by immigrants are not affected by the party affiliation of governors, whereas hourly income is. This suggests that under Democratic governors immigrants have better opportunities to get better paying jobs. Democratic governors have positive and significant effects on hourly income of blacks, but not on other races. Similar pattern holds when the dependent variable is weekly or annual income (coefficients for Img×Dem are 3.9 and 4.2 percents respectively, and statistically significant at 1 percent).

The impact of Democratic governors on labor inputs (presented in columns I through IV) are similar to those reported in Beland (2015). However, our findings that Democratic governors have a positive and significant impact on hourly and weekly income of black workers are different from his, and our analysis shows that these differences mainly stem from studying different time periods.[8] A comparison of the results in Table 2 with Beland's results further indicates that including immigrants does not crowd out the impact of Democratic governors on the labor market outcomes of black workers.

[8]Beland uses the same data sources over the period of 1977–2008, whereas our data cover years from 1993 to 2013. Our sample starts in 1993, following the availability of the immigrant identifier in CPS. When his sample is restricted 1993 to 2008, the coefficients of Black×Dem become positive and statistically significant for hourly and weekly income.

3.4 Possible Channels

In this section, we investigate how Democratic governors can affect immigrants' labor-market outcomes. To the best of our knowledge, we are not aware of any policies that Democratic governors targeted for immigrants. However, the Democratic governors might have implemented policies that improve the labor-market conditions in certain occupations and industries where immigrants are more concentrated.

As discussed in the introduction, recent studies have shown that Democratic governors generally raise minimum wages, spend more on education, health, and state infrastructures, and support unions (Besley and Case, 2003; Reed, 2006; Beland and Oloomi, 2015; Dark, 2001). Applying the RD design to our sample, we also investigate the impact of the party affiliation of the governors on these variables. The results reported in Table A.1 in the appendix are largely consistent with the previous studies.[9]

To this end, we first extend our benchmark specification by including occupation and industry fixed effects,[10] state-level minimum wage, unionization rate, state earned income tax credit (EITC), and state-level per capita government spending.[11] Table 3 presents the regression results based on the extended model. A comparison with Table 2 reveals that the coefficients on the interaction term Img×Dem become substantially smaller (usually at least 50% lower than those in Table 2), and in some cases they are statistically insignificant. For example, total weeks worked and total hours worked are now statistically insignificant. According to Columns I and VII, the estimated coefficients on Img×Dem are about 50% lower than those in Table 2.

Which industries and/or occupations are driving the above results? We run regressions

[9]Although Democrats have strong ties with unions (e.g., Dark, 2001), our analysis shows that the impact of the Democratic Party on unionization rate is very small and insignificant. Our finding is consistent with Beland and Unel (2015) who, using individual level data, find that the party affiliation has no impact on union membership.

[10]We use occ1990 and ind1990 variables in the CPS files that cover several hundred occupations and industries.

[11]Data on government spending on education, health, and highways are available, but we did not include them in the regressions. These series are highly correlated with each other (the coefficient of correlation is at least 0.98) and creating a collinearity problem in our estimations.

Table 3. Impact of Party Affiliation on Labor Markets with All Controls

Variable	Emp Status I	Hours per Week II	Total Weeks III	Total Hours IV	Hourly Income V	Weekly Income VI	Annual Income VII
Dem	−0.0001	0.0034	−0.0003	0.0034	−0.0023	0.0024	0.0030
	(0.0018)	(0.0021)	(0.0012)	(0.0028)	(0.0040)	(0.0043)	(0.0043)
Img×Dem	0.0077**	−0.0076	0.0006	−0.0060	0.0240**	0.0198**	0.0234***
	(0.0038)	(0.0049)	(0.0036)	(0.0076)	(0.0091)	(0.0082)	(0.0083)
Black×Dem	0.0103**	−0.0065	0.0069	0.0012	0.0149	0.0186**	0.0224**
	(0.0040)	(0.0054)	(0.0047)	(0.0089)	(0.0090)	(0.0092)	(0.0101)
Other×Dem	0.0064	0.0020	0.0077	0.0067	0.0045	0.0034	0.0052
	(0.0052)	(0.0050)	(0.0052)	(0.0079)	(0.0086)	(0.0087)	(0.0092)
Img	0.0182***	0.0133***	0.0021	0.0186***	−0.1152***	−0.1121***	−0.1115***
	(0.0037)	(0.0043)	(0.0027)	(0.0055)	(0.0110)	(0.0124)	(0.0121)
Black	−0.0418***	0.0111***	−0.0093***	−0.0006	−0.0194**	−0.0125	−0.0158*
	(0.0028)	(0.0029)	(0.0026)	(0.0048)	(0.0088)	(0.0093)	(0.0094)
Other	−0.0140***	−0.0101***	−0.0154***	−0.0271***	−0.0390***	−0.0288**	−0.0262*
	(0.0029)	(0.0019)	(0.0031)	(0.0042)	(0.0107)	(0.0135)	(0.0136)

Notes: All dependent variables but "Emp Status" are in logs. The data draws on the CPS March samples from IPUMS for the survey years 1994–2014. All regressions include state fixed effects, time effects, and all other control variables specified in equation (1). Numbers in parentheses are standard errors based on clustering data at state level; ***, **, and * represent statistical significance at the 1%, 5%, and 10% level, respectively.

in Table 3 without industry fixed effects, and the results (available upon request) remain mostly the same, suggesting that the impact of the Democratic governors on the labor markets have been mainly through occupational channel. To determine which occupations have played a key role in the results, we split our sample into two sub-samples. The first sample (called Sample 1) includes the following eight (aggregate) occupations that are more likely to be affected by the above policies (such as spending on education, health, and infrastructure, minimum wage, etc): construction, maintenance and repair, farming, food preparation and serving, personal care, health care, teaching, and assemblers and operators. About 62 percent of immigrants hold these occupations (see Table A.2 in the Appendix). The second sample (called Sample 2) includes all other occupations.[12]

Note that except for health care and teaching occupations, these occupations are mainly held by unskilled workers (i.e., those with high-school or less education).[13] Second, except for farming, food preparation and serving, and personal care occupations, unions are relatively strong in other occupations in Sample 1. As a comparison, the fraction of unskilled workers in Sample 2 is less than 30 percent for both natives and immigrants, and the unionization rate among natives and immigrants is less than 10 percent (see Table A.2). Consequently, raising minimum wages, spending on education, health, and infrastructure, providing tax incentives, and the strong association with unions are more likely to have a stronger impact on these occupations.[14]

Table 4.A reports regression results using Sample 1 without including any occupation fixed effects and the control variables introduced in this section. Observe that the estimated coefficients on the interaction term Img$\times$Dem under employment status and earning

[12] Other occupations include managers & CEOs, business & finance specialists, architects & engineers, natural scientists, social scientists & workers, engineering & science technicians, sales specialists, and administrative support. Each sample contains about 800,000 individuals.

[13] As reported in Table A.2, the fraction of unskilled workers in these occupations is substantially higher among immigrants. For example, 85 percent of immigrants who work in construction are unskilled, whereas 65 percent of natives working in construction are unskilled.

[14] Many occupations in Sample 1 are low-wage jobs, and even if individuals working in these occupations are not paid minimum wage, a minimum wage increase still affects the earnings of low-wage workers (see, e.g., Lopresti and Mumford, 2014).

figures are positive, significant, and greater than those reported in Table 2. However, estimated coefficients on labor inputs are not statistically different from zero, suggesting that the corresponding results in Table 2 are driven by the differences between the two samples (i.e., Sample 1 vs. Sample 2).

Table 4.B reports the results again based on Sample 1 including dummies for occupations listed in Sample 1 and control variables such as state minimum wage, state EITC, unionization rate, state-level government spending per capita. Observe that the estimated coefficients on the interaction term Img×Dem under employment status and income variables are positive and significant, but substantially smaller than those in Table 4.A.[15]

We now turn to present results based on Sample 2 (see Table 5). As in Table 4.A, we exclude all occupation fixed effects as well as the control variables introduced in this section. Note that except for employment status, for all other outcome variables the estimated coefficients on the interaction term Img×Dem are statistically insignificant. When we run the same regressions with occupation fixed affects and the above control variables (i.e., minimum wage, state EITC, unionization, etc.), the results (available upon request) qualitatively remain the same.

These findings suggest that the results reported in Tables 2 and 3 are mainly driven by occupations listed in Sample 1. In summary, our analysis presented so far indicates that the positive impact of Democratic governors on immigrants' labor-market outcomes mainly stems from implementing certain policies and creating a business environment that has positive effects on some occupations where immigrants are more concentrated.

4 Sensitivity Analysis

In this section, we investigate the sensitivity of the benchmark results to a number of different specifications. We begin our analysis evaluating the validity of the RD design in the present context; we then check robustness of the results using different conditioning

[15]We also run regressions where we excluded occupation dummies, but kept the control variables introduced in this section. In this case, the impact of Democratic governors on immigrant workers' employment status and income figures is about 25 percent lower than those reported in Table 4.A.

Table 4.A. Impact of Party Affiliation on Labor Markets for Sample 1 Without New Controls

Variable	Emp Status I	Hours per Week II	Total Weeks III	Total Hours IV	Hourly Income V	Weekly Income VI	Annual Income VII
Dem	0.0045	0.0033	0.0066**	0.0099*	0.0084	0.0127	0.0140*
	(0.0035)	(0.0034)	(0.0027)	(0.0054)	(0.0068)	(0.0083)	(0.0080)
Img×Dem	0.0195***	−0.0023	0.0140*	0.0117	0.0556***	0.0514***	0.0535***
	(0.0050)	(0.0062)	(0.0071)	(0.0102)	(0.0145)	(0.0140)	(0.0139)
Black×Dem	0.0237***	0.0000	0.0310***	0.0310**	0.0525***	0.0514***	0.0558***
	(0.0043)	(0.0070)	(0.0063)	(0.0116)	(0.0136)	(0.0158)	(0.0158)
Other×Dem	0.0130**	−0.0038	0.0165**	0.0127	0.0276***	0.0219*	0.0240**
	(0.0051)	(0.0061)	(0.0078)	(0.0115)	(0.0096)	(0.0114)	(0.0119)
Img	0.0149***	0.0116	0.0126***	0.0242***	−0.1934***	−0.1914***	−0.1901***
	(0.0040)	(0.0073)	(0.0034)	(0.0086)	(0.0188)	(0.0189)	(0.0181)
Black	−0.0474***	0.0140***	−0.0295***	−0.0156**	−0.0333*	−0.0243	−0.0331*
	(0.0030)	(0.0031)	(0.0045)	(0.0063)	(0.0175)	(0.0177)	(0.0176)
Other	−0.0130***	0.0070**	−0.0135**	−0.0066	−0.0565**	−0.0539**	−0.0478*
	(0.0039)	(0.0032)	(0.0060)	(0.0062)	(0.0220)	(0.0258)	(0.0251)

Notes: All dependent variables but "Emp Status" are in logs. The data draws on the CPS March samples from IPUMS for the survey years 1994–2014. All regressions include state fixed effects, time effects, and all other control variables specified in equation (1). Numbers in parentheses are standard errors based on clustering data at state level; ***, **, and * represent statistical significance at the 1%, 5%, and 10% level, respectively.

Table 4.B. Impact of Party Affiliation on Labor Markets for Sample 1 With All Controls

Variable	Emp Status I	Hours per Week II	Total Weeks III	Total Hours IV	Hourly Income V	Weekly Income VI	Annual Income VII
Dem	0.0014	0.0021	0.0038	0.0060	0.0036	0.0076	0.0090
	(0.0027)	(0.0032)	(0.0027)	(0.0049)	(0.0045)	(0.0057)	(0.0055)
Img×Dem	0.0122**	−0.0089	0.0009	−0.0079	0.0367***	0.0336***	0.0367***
	(0.0049)	(0.0061)	(0.0078)	(0.0109)	(0.0105)	(0.0098)	(0.0095)
Black×Dem	0.0133**	−0.0057	0.0130*	0.0074	0.0283***	0.0293***	0.0349***
	(0.0051)	(0.0065)	(0.0074)	(0.0124)	(0.0094)	(0.0095)	(0.0093)
Other×Dem	0.0068	−0.0047	0.0078	0.0031	0.0159**	0.0129	0.0154
	(0.0056)	(0.0057)	(0.0086)	(0.0118)	(0.0074)	(0.0097)	(0.0100)
Img	0.0293***	0.0257***	0.0281***	0.0537***	−0.1187***	−0.1098***	−0.1092***
	(0.0036)	(0.0058)	(0.0040)	(0.0076)	(0.0116)	(0.0133)	(0.0126)
Black	−0.0446***	0.0105***	−0.0328***	−0.0222***	−0.0062	0.0036	−0.0032
	(0.0032)	(0.0035)	(0.0050)	(0.0068)	(0.0109)	(0.0112)	(0.0115)
Other	−0.0169***	0.0006	−0.0300***	−0.0294***	−0.0356***	−0.0321**	−0.0281*
	(0.0031)	(0.0027)	(0.0044)	(0.0050)	(0.0107)	(0.0148)	(0.0142)

Notes: All dependent variables but "Emp Status" are in logs. The data draws on the CPS March samples from IPUMS for the survey years 1994–2014. All regressions include state fixed effects, time effects, and all other control variables specified in equation (1). Numbers in parentheses are standard errors based on clustering data at state level; ***, **, and * represent statistical significance at the 1%, 5%, and 10% level, respectively.

Table 5. Impact of Party Affiliation on Labor Markets for Sample 2 Without any Controls

Variable	Emp Status I	Hours per Week II	Total Weeks III	Total Hours IV	Hourly Income V	Weekly Income VI	Annual Income VII
Dem	−0.0006	0.0061**	−0.0019	0.0035	−0.0027	0.0039	0.0041
	(0.0012)	(0.0024)	(0.0019)	(0.0034)	(0.0053)	(0.0056)	(0.0054)
Img×Dem	0.0079**	−0.0021	0.0070	−0.0011	0.0006	−0.0092	−0.0081
	(0.0034)	(0.0061)	(0.0044)	(0.0058)	(0.0134)	(0.0135)	(0.0137)
Black×Dem	0.0121***	−0.0056	0.0100**	0.0015	−0.0137	−0.0003	0.0001
	(0.0041)	(0.0054)	(0.0048)	(0.0082)	(0.0143)	(0.0141)	(0.0149)
Other×Dem	0.0090*	0.0072	0.0118**	0.0134	−0.0175	−0.0081	−0.0071
	(0.0051)	(0.0058)	(0.0049)	(0.0081)	(0.0135)	(0.0122)	(0.0129)
Img	0.0022	−0.0112***	−0.0095**	−0.0252***	−0.1053***	−0.1127***	−0.1119***
	(0.0027)	(0.0034)	(0.0039)	(0.0049)	(0.0110)	(0.0126)	(0.0124)
Black	−0.0351***	0.0005	−0.0114***	−0.0177***	−0.0621***	−0.0645***	−0.0640***
	(0.0033)	(0.0035)	(0.0032)	(0.0047)	(0.0063)	(0.0073)	(0.0072)
Other	−0.0043*	−0.0195***	−0.0126***	−0.0313***	−0.0312**	−0.0130	−0.0123
	(0.0024)	(0.0022)	(0.0035)	(0.0053)	(0.0134)	(0.0163)	(0.0165)

Notes: Sample 1 includes the following occupations: construction, maintenance and repair, farming, food preparation and serving, personal care, health care, teaching, and asemblers and operators. All dependent variables but "Emp Status" are in logs. The data draws on the CPS March samples from IPUMS for the survey years 1994–2014. All regressions include state fixed effects, time effects, and all other control variables specified in equation (1). Numbers in parentheses are standard errors based on clustering data at state level; ***, **, and * represent statistical significance at the 1%, 5%, and 10% level, respectively.

variables and sample sizes. Finally, we investigate whether the results are driven by a subset of immigrants, i.e., we investigate heterogeneity among immigrants.

4.1 Evaluation of the RD Design

In this section, we evaluate the validity of our RD design. The crucial identification assumption in our RD specification (1) is that states where the Democrats barely won are similar to states where the Republicans barely won. We first identify certain characteristics of each state such as proportion of immigrants, proportion of skilled labor, proportion of blacks in the population. Using each of these characteristics as a dependent variable in an RD regression, we investigate whether the estimated coefficient on the dummy variable that a Democrat won is significantly different from zero. Our regressions (presented in Table A.3 in the appendix) indicate that the estimated coefficients are statistically insignificant, suggesting that the aforementioned identification assumption is not violated.[16]

Another important assumption in our RD design is that each candidate has imprecise control over the election result. Since we only observe one election result for each candidate, we cannot *directly* test the validity of this assumption. One easy way is to look at the histogram of the MV presented in Figure 1, and see whether there is any unusual jump at the cutoff. According to Figure 1, we do not observe any unusual jumps. A more formal approach is to use the density test proposed by McCrary (2008). Conditions for identification in the regression discontinuity design are continuity of the conditional expectation of counterfactual outcomes in the running variable. These continuity assumptions may not be plausible if agents are able to manipulate the running variable. McCrary (2008) developed a test of manipulation related to continuity of the running variable density function. Figure 3 represents the density function of the MV according to the procedure outlined

[16] More specifically, for each state characteristics C, we estimate

$$C_{st} = \beta_o + \beta_s + \beta_t + \beta_D D_{st} + F(MV_{st}) + \varepsilon_{st}.$$

If states around the discontinuity are similar, one can expect that the estimated coefficient β_D must be statistically insignificant.

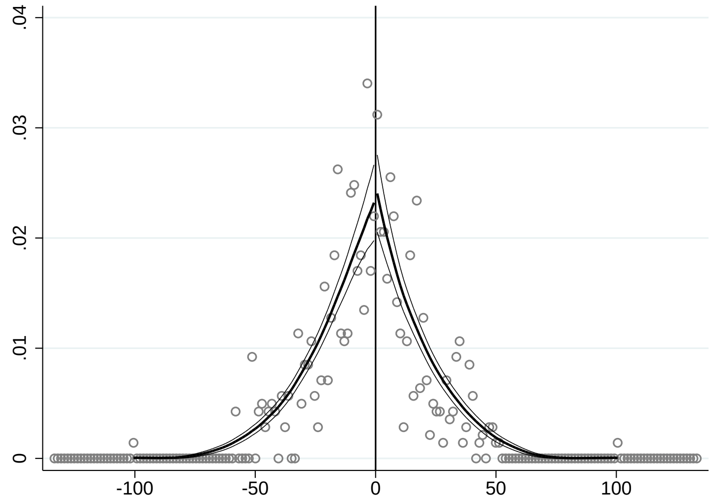


FIGURE 3. Density Function of the Margin of Victory (McCrary test)

in McCrary (2008), and there are no unusual jumps around the cutoff.[17]

As emphasized by Lee and Lemieux (2014), one should explore the robustness of the results to a range of orders of the polynomials and a range of bandwidths. In our main specifications, following Gelman and Imbens (2014), we use a second-order polynomial function for $F(MV)$. We also considered first-, third-, and fourth-order of polynomial functions. Table A.4 in the appendix, for example, presents results based on the third-order polynomial specification, and its comparison with Table 2 indicate that our results are not sensitive to the degree of the polynomial.[18] We also consider non-parametric regression discontinuity using optimal bandwidth procedures of Calonico et al. (2012) and Imbens and Kalyanaraman (2012). Table A.5 reports the results for the local-linear specifications using grouped data by state and year, and its comparison with Table 2

[17] We also verified that states where Democrats barely won and states where Democrats barely lost are not statistically different from each other in their pre-treatment covariates. To address the issues raised in Caughey and Sekhon (2011), using data from Jensen and Beyle (2003), we found that campaign spending is not different when Democrats barely wins than when they barely lost. In addition, for close elections to be regarded as random, such elections won by Democratic governors should not be more likely to come with a Democratic House or Senate. We checked and confirmed that those variables are not statistically different when Democrats barely won.

[18] The results based on first- and fourth-order polynomial specifications (available upon request) are qualitatively similar.

indicate that they are robust across different specifications.

Another identification concern is the persistence of the outcome variables. For example, if Democratic governors are more likely to be elected in state-years when immigrants and/or minorities have better labor market inputs, the RD designs yield biased estimates. To determine whether this is the case, we use a placebo test where we replace the outcome variable in specification (1) with the corresponding variable measured one "term" ago, and check for the balance between the control and treatment group. The regression results (presented in Table A.6) show that the coefficients of interest are not significant, suggesting no discontinuity in the last term outcome.

The Democratic Party has some conservative members whose political views are similar to Republican counterparts, and they are mainly found in the Southern states. We next investigate the impact of party affiliation on the labor-market outcomes when the Southern states are excluded in the sample.[19] Table A.7 in the appendix reports the results based on this restricted sample, and the results are similar to those reported in Table 2.

It can be argued that governors are more likely to make a difference when they are matched with legislatures that are of the same party. Consequently, we also investigate the impact of party affiliation on immigrants' labor-market outcomes when both governors and legislatures are from the same party. However, our RD analysis (available upon request) yields qualitatively the same results.

In addition, we also considered specifications with more controls. We included a dummy for the governor being a woman or from a non-white race. We also controlled for the party that controls the state House and Senate. The results (available upon request) are similar to those presented in Table 2. Finally, we also include region specific time effects in our specifications, but the results remain mostly the same.

[19]We use the Census bureau definition of southern states, which are Alabama, Arkansas, Delaware, Florida, Georgia, Kentucky, Louisiana, Maryland, Mississippi, North Carolina, Oklahoma, South Carolina, Tennessee, Texas, Virginia and West Virginia.

4.2 Heterogeneity Across Immigrants

As indicated in the previous section, about 40% of immigrants are not citizens. How do the party affiliations of governors affect labor-market outcomes of citizen and non-citizen immigrants? We extend specification (1) by replacing the immigration variable with two variables: one for citizen immigrants and one for non-citizen immigrants (denoted by Img_c and Img_nc, respectively) together with all corresponding interaction terms with the variable Dem and polynomial functions $F(MV)$. Table A.8 in the appendix reports the results based on this extended model. Note that non-citizen immigrants make substantially less than native, white workers (about 27 percent less). Note further that under Democratic governors the income of citizen immigrants increases by about 2.2%, whereas the income of non-citizen immigrants by about 4.3%. The income differences between these two groups are statistically significant at the 5% level. The impact of Democratic governors on other labor-market outcomes across these groups are largely the same.

We consider heterogeneity among immigrants in two other dimensions as well: skilled vs. unskilled immigrants and female vs. male immigrants. Everyone who has high school or less education is considered as unskilled, and those who have at least some college education are classified as skilled. In our sample, about 55% of immigrants are unskilled. As Table A.8 in the appendix shows, except for "Hours per Week," Democratic governors have a positive and statistically significant impact on labor-market outcomes of skilled and unskilled immigrants. In addition, for each outcome the estimated coefficients on the interaction terms Img_s×Dem and Img_u×Dem are not statistically different from each other. We obtain qualitatively the same conclusion when we study the impact of the party affiliation on the labor-market outcomes of male and female immigrants (see Table A.10 in the appendix).

5 Conclusion

Immigration has become a pressing issue for politicians in the U.S., because immigrants have been playing increasingly significant role in the economy and politics. There is a large literature in labor economics that studies the interaction between immigration and labor markets in the U.S. mainly focusing on the impact of immigration on income inequality and unemployment. The literature has also documented that immigrants have lower incomes and higher unemployment rates relative to natives. When it comes to political party preferences, immigrants have overwhelmingly voted for the Democratic party. Naturally one wonders whether immigrants are economically better off under the Democratic Party.

Using more than 250 gubernatorial elections in 50 states between 1993 and 2013, this paper investigated the causal impact of the party affiliations of U.S. governors on immigrants' labor-market outcomes. We implemented a regression discontinuity (RD) design by exploiting the variation associated with close elections. Our analysis shows that immigrants have experienced different labor-market outcomes under the Democratic Party. In particular, we found that immigrants are more likely to be employed, work longer hours and more weeks, and have higher earnings under Democratic governors. We also found that the party affiliation of governors generally has no impact on the corresponding outcomes of white natives.

Our analysis present evidence that Democratic governors implement policies (such as raising state-level minimum wages, increasing government spending on health, education, infrastructure, providing tax credit for low income people, etc) that create better labor-market conditions in certain occupations where immigrants are concentrated. Our extensive sensitivity analysis shows that the results are robust to a number of different specifications, controls, and samples.

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Conflict of Interest: The authors declare that they have no conflict of interest.

References

Alesina, Alberto, Reza Baqir, and William Easterly, "Public Goods and Ethnic Divisions," *Quarterly Journal of Economics*, 1999, *114*, 1234–84.

Alt, James E. and Robert C. Lowry, "A Dynamic Model of State Budget Outcomes under Divided Partisan Government," *Journal of Politics*, 2000, *62* (4), 1035–69.

Autor, David H., Lawrence F. Katz, and Melissa S. Kearney, "Trends in U.S. Wage Inequality: Revising the Revisionists," *Review of Economics and Statistics*, 2008, *90*, 300–23.

Beland, Louis-Philippe, "Political Parties and Labor Market Outcomes. Evidence from U.S. States," *American Economic Journal: Applied Economics*, 2015, *7*, 1–26.

___ **and Bulent Unel**, "Democrats and Unions," *LSU Working Paper*, 2015.

___ **and Sara Oloomi**, "Party Affiliation and Public Spending," *LSU Working paper*, 2015.

Besley, Timothy and Anne Case, "Does Electoral Accountability Affect Economic Policy Choices? Evidence from Gubernatorial Term Limits," *The Quarterly Journal of Economics*, 1995, *110* (3), 769–798.

___ **and** ___ , "Political Institutions and Policy Choices: Evidence from the United States," *Journal of Economic Literature*, 2003, *41* (1), pp. 7–73.

Borjas, George, "The Labor Demand Curve is Downward Sloping: Reexamining the Impact of Immigration on the Labor Market," *Quarterly Journal of Economics*, 2003, *118*, 1335–74.

Calonico, Sebastian, Matias D Cattaneo, and Rocio Titiunik, "Robust Data-Driven Inference in the Regression-Discontinuity Design," *Stata Journal*, 2012, *55* (2), 1–29.

Card, David, "Immigrant Inflows, Native Outflows, and the Local Market Impacts of Higher Immigration," *Journal of Labor Economics*, 2001, *19*, 22–64.

___ , "Immigrant and Inequality," *American Economic Review: Papers & Proceedings*, 2009, *99*, 1–21.

Caughey, Devin and Jasjeet S. Sekhon, "Elections and the Regression Discontinuity Design: Lessons from Close US House Races, 1942–2008," *Political Analysis*, 2011, *19*, 385–408.

Congressional Budget Office, *A Description of Immigration Population*, Washington, DC: CBO, 2013.

Cortes, Patricia, "The Effect of Low-skilled Immigration on US Prices: Evidence from CPI Data," *Journal of Political Economy*, 2008, *116*, 381–422.

Damm, Anna Piil, "Neighborhood quality and labor market outcomes: Evidence from quasi-random neighborhood assignment of immigrants," *Journal of Urban Economics*, 2014, *79*, 139–166.

Dark, Taylor E., *The Unions and the Democrats: An Enduring Alliance*, Ithaca, NY: Cornell University Press, 2001.

Ferreira, Fernando and Joseph Gyourko, "Do Political Parties Matter? Evidence from U.S. Cities," *Quarterly Journal of Economics*, 2009, *124* (1), 399–422.

Garand, James C., "Explaining Government Growth in the U.S. States," *The American Political Science Review*, 1988, *82*, 837–849.

Gelman, Andrew and Guido Imbens, "Why High-Order Polynomials Should Not be Used in Regression Discontinuity Designs," *NBER Working paper No. 20405*, 2014.

Hunt, Jennifer and Marjolaine Gauthier-Loiselle, "How Much Does Immigration Boost Innovation?," *American Economic Journal: Macroeconomics*, 2010, *2*, 31–56.

___ **and Rachek Friedberg**, "Immigrants and the Receiving Economies," in C. Hirschman, P. Kasinitz, and J. DeWind, eds., *Handbook of International Migration: The American Experience*, Russell Sage Foundation, 1999.

Imbens, Guido and Karthik Kalyanaraman, "Optimal Bandwidth Choice for the Regression Discontinuity Estimator," *Review of Economic Studies*, 2012, *79* (3), 933–959.

Jensen, Jennifer M and Thad Beyle, "Of footnotes, missing data, and lessons for 50-state data collection: The gubernatorial campaign finance data project, 1977–2001," *State Politics & Policy Quarterly*, 2003, *3* (2), 203–214.

King, Miriam, Steven Ruggles, J. Trent Alexander, Sarah Flood, Katie Genadek, Matthew B. Schroeder, Brandon Trampe, and Rebecca Vick, *Integrated Public Use Microdata Series, Current Population Survey: Version 3.0 [Machine-readable database]*, Minneapolis, MN: University of Minnesota, 2010.

Knight, Brian, "Supermajority Voting Requirements for Tax Increases: Evidence from the States," *Journal of Public Economics*, 2000, *76*, 41–67.

Lee, David S., "Randomized Experiments from Non-random Selection in U.S. House Elections," *Journal of Econometrics*, 2008, *142* (2), 675–697.

___ **and Thomas Lemieux**, "Regression Discontinuity Designs in Economics," *Journal of Economic Literature*, June 2010, *48* (2), 281–355.

___ **and** ___ , "Regression Discontinuity Designs in the Social Sciences," in H. Best and C. Wolf, eds., *Regression Analysis and Causal Inference*, Sage, 2014.

___ **, Enrico Moretti, and Matthew J. Butler**, "Do Voters Affect or Elect Policies? Evidence from the U. S. House," *Quarterly Journal of Economics*, 2004, *119* (3), pp. 807–859.

Leigh, Andrew, "Estimating the Impact of Gubernatorial Partisanship on Policy Settings and Economic Outcomes: A Regression Discontinuity Approach," *European Journal of Political Economy*, 2008, *24* (1), 256–268.

Leip, David, *Dave Leip's Atlas of U.S. Presidential Elections.*, http://uselectionatlas.org, 2015.

Lewis, Ethan G., "Immigration, Skill Mix, and Capital Skill Complementarity," *Quarterly Journal of Economics*, 2011, *126*, 1029–69.

Lopresti, John W. and Kevin J. Mumford, "Who Benefits from a Minimum Wage Increase?," *Purdue University Working Paper*, 2014.

McCrary, Justin, "Manipulation of the running variable in the regression discontinuity design: A density test," *Journal of Econometrics*, 2008, *142* (2), 698–714.

McHenry, Peter, "Immigration and the Human Capital of Natives," *Journal of Human Resources*, 2015, *50*, 34–71.

Ottaviano, Gianmarco I. P. and Giovanni Peri, "Rethinking the Effects of Immigration on Wages," *Journal of the European Economic Association*, 2012, *10*, 152–97.

Peri, Giovanni, "The Effect of Immigration on Productivity: Evidence from U.S. States," *Review of Economics and Statistics*, 2012, *94*, 348–58.

Petrocik, John R., "Measuring Party Support: Leaners are not Independents," *Electoral Studies*, 2009, *28* (4), 562–72.

Pettersson-Lidbom, Per, "Do Parties Matter for Economic Outcomes? A Regression-Discontinuity Approach," *Journal of the European Economic Association*, 2008, *6* (5), 1037–56.

Preston, Ian, "The Effect of Immigration on Public Finances," Technical Report, CReAM Discussion Paper 2013.

Razin, Assaf, Efraim Sadka, and Phillip Swagel, "Tax Burden and Migration: a Political Economy Theory and Evidence," *Journal of Public Economics*, 2002, *85*, 167–90.

Reed, W. Robert, "Democrats, Republicans, and Taxes: Evidence That Political Parties Matter," *Journal of Public Economics*, 2006, *90* (4-5), 725–750.

Solé-Ollé, Albert and Elisabet Viladecans-Marsal, "Do political parties matter for local land use policies?," *Journal of Urban Economics*, 2013, *78*, 42–56.

U.S. Bureau of Economic Analysis, *Table 2.3.4. Price Indexes for Personal Consumption Expenditure by Major Type of Product*, Washington, DC: BEA, 2014.

Appendix

Table A.1 Impact of Party Affiliation on Policy Variables

Variable	Min Wage	Expenditure: Education	Expenditure: Health	Expenditure: Highway	Expenditure: Total	Union Rate	State EITC
Dem	0.0654*	0.0276**	0.1391**	0.0972**	0.1565**	0.0024	0.0820
	(0.0387)	(0.0113)	(0.0650)	(0.0441)	(0.0710)	(0.0015)	(0.5582)

Notes: The independent variable is the dummy variable Dem. Expenditure are in logs. Numbers in parentheses are standard errors based on clustering data at state level; ***, **, and * represent statistical significance at the 1%, 5%, and 10% level, respectively.

Table A.2 Summary Statistics for Immigrants and White Natives (%)

Occupation	Immigrants	White Natives	Unskilled Workers: Immigrants	Unskilled Workers: Natives	Unionization Rate: Immigrants	Unionization Rate: Natives
Construction	8.7	5.1	84.8	67.3	18.8	22.7
Education	3.2	6.0	8.3	7.8	42.7	39.4
Farming	4.4	1.8	91.8	64.0	4.4	3.7
Food Service	7.8	4.7	77.9	61.7	6.1	4.4
Health	7.2	6.9	26.5	23.1	17.5	11.5
Operators	18.9	14.2	77.1	67.9	18.1	19.9
Personal care	6.0	3.1	73.4	54.5	9.3	7.0
Repair	6.1	5.3	72.7	61.3	18.0	17.8
Others	37.8	52.9	28.5	30.0	9.1	8.5

Notes: Table A.2 presents summary statistics for fraction of immigrants and white natives working in each occupation group. It also presents the fraction of immigrants and white natives that are unskilled and unionized in each occupation group. Everyone who has high school or less education is considered as unskilled.

Table A.3 Regression Discontinuity: Characteristics of States

Variable	Black	Other	Img	Female	Skilled	Unskilled
Dem	-0.0025	-0.0006	-0.0031	-0.0012	0.0045	0.0005
	(0.0019)	(0.0025)	(0.0035)	(0.0013)	(0.0029)	(0.0034)

Notes: The data draws on the CPS March samples from IPUMS for the survey years 1994–2014. Outcome variables are characteristics of states: proportion of population that is: Black, Other race, Immigrants, Female, Skilled and Unskilled. Numbers in parentheses are standard errors based on clustering data at state level; ***, **, and * represent statistical significance at the 1%, 5%, and 10% level, respectively.

Table A.4 Robustness: Using Third-Order Polynomial Specification for $F(MV)$

Variable	Emp Status I	Hours per Week II	Total Weeks III	Total Hours IV	Hourly Income V	Weekly Income VI	Annual Income VII
Dem	0.0031	0.0058*	0.0045**	0.0103**	0.0011	0.0078	0.0090
	(0.0026)	(0.0031)	(0.0019)	(0.0043)	(0.0059)	(0.0061)	(0.0061)
Img×Dem	0.0126***	−0.0011	0.0136***	0.0148*	0.0324***	0.0298**	0.0325***
	(0.0035)	(0.0051)	(0.0044)	(0.0086)	(0.0114)	(0.0119)	(0.0119)
Black×Dem	0.0167***	−0.0008	0.0255***	0.0263***	0.0251*	0.0225	0.0254*
	(0.0033)	(0.0058)	(0.0052)	(0.0096)	(0.0131)	(0.0144)	(0.0146)
Other×Dem	0.0102**	0.0041	0.0195***	0.0221**	0.0093	0.0086	0.0100
	(0.0048)	(0.0052)	(0.0061)	(0.0089)	(0.0137)	(0.0149)	(0.0151)
Img	0.0065*	−0.0037	−0.0044*	−0.0046	−0.1867***	−0.1939***	−0.1911***
	(0.0037)	(0.0049)	(0.0026)	(0.0061)	(0.0169)	(0.0173)	(0.0168)
Black	−0.0395***	0.0071**	−0.0250***	−0.0215***	−0.0420**	−0.0399**	−0.0441**
	(0.0024)	(0.0035)	(0.0033)	(0.0058)	(0.0182)	(0.0187)	(0.0183)
Other	−0.0062	−0.0021	−0.0116**	−0.0147**	−0.0744***	−0.0653***	−0.0604***
	(0.0039)	(0.0021)	(0.0052)	(0.0071)	(0.0206)	(0.0224)	(0.0225)

Notes: All dependent variables but "Emp Status" are in logs. The data draws on the CPS March samples from IPUMS for the survey years 1994–2014. All regressions include state fixed effects, time effects, and all other control variables specified in equation (1). Numbers in parentheses are standard errors based on clustering data at state level; ***, **, and * represent statistical significance at the 1%, 5%, and 10% level, respectively.

Table A.5 Local-Linear Analysis

	Emp Status	Total Hours	Annual Income
A. White Natives			
Imbens and Kalyanaraman (2012)	0.0001	−0.0010	−0.0107
	(0.0005)	(0.0018)	(0.0128)
h	10.27	9.90	10.51
Calonico et al. (2012)	−0.0001	−0.0019	−0.0142
	(0.0005)	(0.0016)	(0.0120)
h	12.5	12.09	12.53
B. Immigrants			
Imbens and Kalyanaraman (2012)	0.0108***	0.0152*	0.0750**
	(0.0039)	(0.0082)	(0.0347)
h	17.63	14.10	12.32
Calonico et al. (2012)	0.0108***	0.0146*	0.0771**
	(0.0039)	(0.0077)	(0.0336)
h	17.66	16.06	13.71

Notes: The independent variable is the dummy variable Dem. Numbers in parentheses are standard errors based on clustering data at state level; h is the optimal bandwith; ***, **, and * represent statistical significance at the 1%, 5%, and 10% level, respectively.

Table A.6 Robustness: Using the Previous Term Election Results

Variable	Emp Status I	Hours per Week II	Total Weeks III	Total Hours IV	Hourly Income V	Weekly Income VI	Annual Income VII
Dem	−0.00173	−0.00143	−0.00201	−0.00187	−0.00526	−0.00787	−0.00521
	(0.00281)	(0.00249)	(0.00287)	(0.00510)	(0.00591)	(0.00699)	(0.00959)
Img×Dem	0.00313	$-7.03e{-}05$	0.00496	0.00170	0.00843	0.0116	0.00675
	(0.00367)	(0.00376)	(0.00543)	(0.00751)	(0.0109)	(0.0110)	(0.0147)
Black×Dem	0.00187		0.00285	−0.00524	−0.0122		−0.0153
	(0.00471)		(0.00516)	(0.00788)	(0.00866)		(0.0111)
Other×Dem	0.000534	−0.00190	−0.000300	−0.00502	−0.0174	−0.0157	−0.0194
	(0.00526)	(0.00546)	(0.00953)	(0.0146)	(0.0108)	(0.00969)	(0.0152)
Img	0.00443	−0.00789	−0.00434	−0.0107	−0.215***	−0.231***	−0.240***
	(0.00356)	(0.00489)	(0.00380)	(0.00776)	(0.0238)	(0.0244)	(0.0272)
Black	−0.0407***	0.00217	−0.0281***	−0.0223***	−0.0658***	−0.0775***	−0.0959***
	(0.00334)	(0.00277)	(0.00367)	(0.00613)	(0.0122)	(0.0109)	(0.0141)
Other	−0.00680	−0.00221	−0.0110	−0.0120	−0.115***	−0.114***	−0.138***
	(0.00503)	(0.00311)	(0.00845)	(0.0113)	(0.0210)	(0.0243)	(0.0242)

Notes: All dependent variables but "Emp Status" are in logs. The data draws on the CPS March samples from IPUMS for the survey years 1994–2014. All regressions include state fixed effects, time effects, and all other control variables specified in equation (1). Numbers in parentheses are standard errors based on clustering data at state level; ***, **, and * represent statistical significance at the 1%, 5%, and 10% level, respectively.

Table A.7 Robustness: Excluding Southern States

Variable	Emp Status I	Hours per Week II	Total Weeks III	Total Hours IV	Hourly Income V	Weekly Income VI	Annual Income VII
Dem	0.0033	0.0038	0.0049**	0.0094*	0.0036	0.0082	0.0095
	(0.0023)	(0.0039)	(0.0024)	(0.0051)	(0.0059)	(0.0069)	(0.0068)
Img×Dem	0.0156***	−0.0079	0.0131**	0.0075	0.0374**	0.0316**	0.0342**
	(0.0028)	(0.0053)	(0.0051)	(0.0095)	(0.0139)	(0.0144)	(0.0143)
Black×Dem	0.0142***	0.0005	0.0236***	0.0276**	0.0252**	0.0248*	0.0283**
	(0.0029)	(0.0058)	(0.0060)	(0.0108)	(0.0114)	(0.0131)	(0.0133)
Other×Dem	0.0100*	0.0048	0.0154**	0.0196*	0.0208*	0.0215*	0.0232*
	(0.0056)	(0.0051)	(0.0066)	(0.0101)	(0.0108)	(0.0118)	(0.0122)
Img	0.0028	0.0038	−0.0036	0.0033	−0.2011***	−0.2022***	−0.1989***
	(0.0032)	(0.0034)	(0.0032)	(0.0055)	(0.0232)	(0.0242)	(0.0234)
Black	−0.0411***	0.0090*	−0.0258***	−0.0219***	−0.0384*	−0.0349	−0.0399*
	(0.0029)	(0.0047)	(0.0036)	(0.0078)	(0.0214)	(0.0222)	(0.0219)
Other	−0.0066	−0.0031	−0.0087	−0.0132	−0.0795***	−0.0683**	−0.0625**
	(0.0045)	(0.0030)	(0.0059)	(0.0094)	(0.0256)	(0.0291)	(0.0290)

Notes: The sample excludes Alabama, Arkansas, Delaware, Florida, Georgia, Kentucky, Louisiana, Maryland, Mississippi, North Carolina, Oklahoma, South Carolina, Tennessee, Texas, Virginia and West Virginia. All dependent variables but "Emp Status" are in logs. The data draws on the CPS March samples from IPUMS for the survey years 1994–2014. All regressions include state fixed effects, time effects, and all other control variables specified in equation (1). Numbers in parentheses are standard errors based on clustering data at state level; ***, **, and * represent statistical significance at the 1%, 5%, and 10% level, respectively.

Table A.8 Robustness: Citizen vs Non-citizen Immigrants

Variable	Emp Status I	Hours per Week II	Total Weeks III	Total Hours IV	Hourly Income V	Weekly Income VI	Annual Income VII
Dem	0.0017	0.0035	0.0010	0.0049	0.0001	0.0043	0.0050
	(0.0020)	(0.0025)	(0.0018)	(0.0040)	(0.0055)	(0.0062)	(0.0061)
Img_c×Dem	0.0115***	0.0029	0.0110**	0.0157*	0.0207*	0.0217*	0.0244**
	(0.0035)	(0.0053)	(0.0045)	(0.0088)	(0.0104)	(0.0118)	(0.0117)
Img_nc×Dem	0.0161***	−0.0044	0.0118**	0.0108	0.0460***	0.0406***	0.0437***
	(0.0042)	(0.0053)	(0.0048)	(0.0079)	(0.0148)	(0.0143)	(0.0145)
Black×Dem	0.0187***	−0.0013	0.0234***	0.0243**	0.0303**	0.0273*	0.0303**
	(0.0034)	(0.0053)	(0.0054)	(0.0093)	(0.0131)	(0.0140)	(0.0145)
Other×Dem	0.0119**	0.0033	0.0184***	0.0209**	0.0155	0.0139	0.0155
	(0.0050)	(0.0049)	(0.0062)	(0.0088)	(0.0145)	(0.0156)	(0.0160)
Img_c	0.0117***	0.0085*	0.0152***	0.0280***	−0.0924***	−0.0939***	−0.0944***
	(0.0024)	(0.0045)	(0.0025)	(0.0066)	(0.0135)	(0.0150)	(0.0146)
Img_nc	−0.0006	−0.0160***	−0.0191***	−0.0330***	−0.2679***	−0.2810***	−0.2761***
	(0.0047)	(0.0056)	(0.0025)	(0.0061)	(0.0186)	(0.0188)	(0.0182)
Black	−0.0423***	0.0035	−0.0273***	−0.0280***	−0.0613***	−0.0611***	−0.0651***
	(0.0022)	(0.0030)	(0.0032)	(0.0054)	(0.0142)	(0.0149)	(0.0147)
Other	−0.0089**	−0.0063***	−0.0157***	−0.0237***	−0.0630***	−0.0534**	−0.0492**
	(0.0035)	(0.0018)	(0.0046)	(0.0059)	(0.0193)	(0.0201)	(0.0203)

Notes: All dependent variables but "Employed" are in logs. The data draws on the CPS March samples from IPUMS for the survey years 1994–2014. All regressions include state fixed effects, time effects, and all other control variables specified in equation (1). Numbers in parentheses are standard errors based on clustering data at state level; ***, **, and * represent statistical significance at the 1%, 5%, and 10% level, respectively.

Table A.9 Robustness: Skilled vs Unskilled Immigrants

Variable	Emp Status I	Hours per Week II	Total Weeks III	Total Hours IV	Hourly Income V	Weekly Income VI	Annual Income VII
Dem	0.0021	0.0038	0.0016	0.0060	−0.0007	0.0038	0.0046
	(0.0020)	(0.0026)	(0.0018)	(0.0039)	(0.0058)	(0.0066)	(0.0065)
Img_s×Dem	0.0153***	0.0011	0.0175***	0.0207**	0.0307**	0.0298**	0.0312**
	(0.0039)	(0.0054)	(0.0045)	(0.0090)	(0.0118)	(0.0130)	(0.0132)
Img_u×Dem	0.0182***	0.0010	0.0108**	0.0173**	0.0298**	0.0260*	0.0269*
	(0.0040)	(0.0061)	(0.0047)	(0.0072)	(0.0145)	(0.0152)	(0.0148)
Black×Dem	0.0211***	0.0015	0.0254***	0.0302***	0.0271**	0.0258**	0.0276**
	(0.0033)	(0.0048)	(0.0054)	(0.0087)	(0.0114)	(0.0126)	(0.0126)
Other×Dem	0.0131**	0.0054	0.0183***	0.0237***	0.0101	0.0102	0.0114
	(0.0049)	(0.0046)	(0.0066)	(0.0086)	(0.0121)	(0.0130)	(0.0131)
Img_s	−0.0016	−0.0053	−0.0080**	−0.0120*	−0.1162***	−0.1222***	−0.1226***
	(0.0030)	(0.0042)	(0.0030)	(0.0070)	(0.0135)	(0.0143)	(0.0143)
Img_u	0.0104**	−0.0066	−0.0019	−0.0038	−0.2773***	−0.2855***	−0.2822***
	(0.0049)	(0.0065)	(0.0031)	(0.0071)	(0.0230)	(0.0240)	(0.0232)
Black	−0.0407***	0.0047	−0.0250***	−0.0242***	−0.0652***	−0.0650***	−0.0675***
	(0.0022)	(0.0030)	(0.0031)	(0.0054)	(0.0138)	(0.0147)	(0.0148)
Other	−0.0054	−0.0037**	−0.0106**	−0.0152**	−0.0530***	−0.0438**	−0.0411**
	(0.0035)	(0.0018)	(0.0051)	(0.0067)	(0.0183)	(0.0200)	(0.0198)

Notes: All dependent variables but "Employed" are in logs. The data draws on the CPS March samples from IPUMS for the survey years 1994–2014. All regressions include state fixed effects, time effects, and all other control variables specified in equation (1). Numbers in parentheses are standard errors based on clustering data at state level; ***, **, and * represent statistical significance at the 1%, 5%, and 10% level, respectively.

Table A.10 ROBUSTNESS: FEMALE VS MALE IMMIGRANTS

Variable	Emp Status I	Hours per Week II	Total Weeks III	Total Hours IV	Hourly Income V	Weekly Income VI	Annual Income VII
Dem	0.0021	0.0036	0.0016	0.0057	0.0014	0.0055	0.0061
	(0.0020)	(0.0025)	(0.0018)	(0.0039)	(0.0057)	(0.0065)	(0.0063)
Img_f×Dem	0.0148***	−0.0034	0.0143***	0.0144	0.0363***	0.0310**	0.0331**
	(0.0041)	(0.0059)	(0.0047)	(0.0089)	(0.0120)	(0.0132)	(0.0133)
Img_m×Dem	0.0165***	0.0027	0.0154**	0.0201**	0.0403***	0.0395***	0.0429***
	(0.0040)	(0.0059)	(0.0060)	(0.0100)	(0.0133)	(0.0136)	(0.0138)
Black×Dem	0.0202***	0.0007	0.0270***	0.0296***	0.0311**	0.0288**	0.0318**
	(0.0031)	(0.0055)	(0.0053)	(0.0092)	(0.0126)	(0.0138)	(0.0143)
Other×Dem	0.0124***	0.0051	0.0204***	0.0241***	0.0138	0.0132	0.0148
	(0.0046)	(0.0050)	(0.0059)	(0.0086)	(0.0137)	(0.0149)	(0.0153)
Img_f	0.0137***	−0.0190***	0.0013	−0.0157***	−0.2258***	−0.2465***	−0.2420***
	(0.0038)	(0.0048)	(0.0021)	(0.0055)	(0.0184)	(0.0192)	(0.0187)
Img_m	−0.0079**	0.0121**	−0.0135***	0.0029	−0.1636***	−0.1551***	−0.1548***
	(0.0030)	(0.0060)	(0.0037)	(0.0086)	(0.0186)	(0.0196)	(0.0189)
Black	−0.0412***	0.0040	−0.0252***	−0.0253***	−0.0561***	−0.0561***	−0.0602***
	(0.0022)	(0.0031)	(0.0031)	(0.0055)	(0.0148)	(0.0154)	(0.0151)
Other	−0.0066	−0.0049***	−0.0111*	−0.0175**	−0.0820***	−0.0733***	−0.0686***
	(0.0041)	(0.0018)	(0.0056)	(0.0073)	(0.0208)	(0.0232)	(0.0232)

Notes: All dependent variables but "Employed" are in logs. The data draws on the CPS March samples from IPUMS for the survey years 1994–2014. All regressions include state fixed effects, time effects, and all other control variables specified in equation (1). Numbers in parentheses are standard errors based on clustering data at state level; ***, **, and * represent statistical significance at the 1%, 5%, and 10% level, respectively.