Local Demographic Changes and US Presidential Voting, 2012-2016: A Replication

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4/25/2020

Contents

1 Abstract

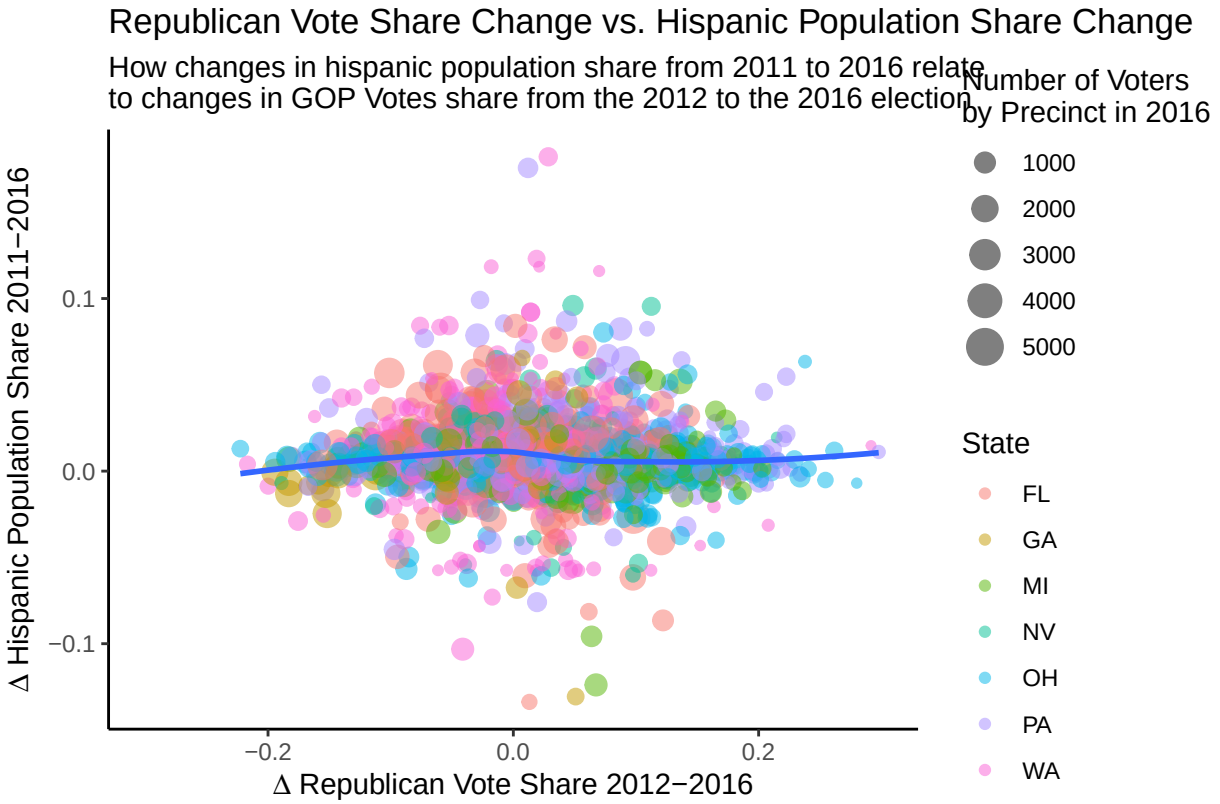
Hilla, Hopkins, and Huberc (2019) argue that demographic changes are not associated with increased Republican vote share at the precinct level between 2012 and 2016. I succesfully replicated Hilla, Hopkins and Huberc's results, except for minor discrepancies which do not affect their conclusions. A robustness test using a subset analysis focusing on the state of FL indicates, despite minor state-specific deviance and poor statistical significance due to reduced sample size, that the authors' overall findings are valid. Another test focusing on the effect of individual states on the overall findings was also found to support the original paper's robustness. In addition, I constructed a fixed effects model by state, which further confirmed original findings even under fixed effects assumptions. In a twist of analysis, I constructed a new model analyzing the association between Republican vote share and economic indicators while controlling for Hispanic proportion. The latter models appear to indicate a stronger relationship between unemployment proportion change and GOP vote share than between changes in Hispanic proportion and GOP vote share, which suggests an opportunity for further research.

2 Introduction

Immigration and demographic changes have become salient in American political discourse in great part due to Trump's capaign for tthe 2016 election. Inspired by previous inconclusive research on threatened response and county-level electoral outcomes, Hilla, Hopkins, and Huberc, henceforth HHH, compiled a novel, precinct-level data set of election results and census demographic measures for almost 32,000 precincts across 7 states to explore how demographic changes influenced republican vote share in affected precincts across the United States. The authors employed regression models with varying explanatory variables and measures of demographic change. Through this analysis, the authors find consistent evidence that 'influxes of Hispanics or non-citizen immigrants' were associated with decreased Republican vote share, which was assumed by the authors to mean shifts towards Trump's opponent in 2016 (Hilla, Hopkins, and Huberc 2019). Dan Hopkins offers an overview and a link to the data for this research paper on his website. The full original paper can be found here.

Using R and RStudio, I succesfully replicated HHH's results, except for minor discrepancies which do not affect their conclusions (R Core Team 2017). Some of these discepancies can be associated with the inherent assumptions of the Stata software versus R. The replication process was lengthy and focused mainly on translating local variables from Stata (the coding language in which the original analysis was conducted) into R using the original datasets to construct the main eight models supporting the argument. A step by step replication of the 8 main models and graphics of the paper are included in the appendix. Thanks to the generosity of the authors the code and data used in this project are available at Harvard Dataverse. For more information about this project please visit my project's Github repo[1].

[1]The data and code for this project can be found here.



Source: HHH Demographic Threat Data Archive: Geo_Scope

A visual association between changes of Republican Vote Share and Hispanic Population Proportion Change from 2012-2016. Random sample of 2000 precincts colored by state (Wickham et al. 2019). A loess line highlights the general trend of the data (Consulting 2020). I also added the aesthetic enhancement of size as number of voters in 2016 in each precinct (Xie, Allaire, and Grolemund 2019).

I determined two main ways to examine the robustness of these models: 1) I examined the model outputs at higher level of aggregation by constructing the same models using a subset of data by state. In this case, I used Florida, which is my home state and one that has received a very high influx of hispanics over the last decade. Despite, the smaller sample, which inherently causes decreased statistical significance, HHH's overall conclusions are validated. In addition, I constructed a series of models excluding a different state each time to examine whether any single state was shaping the conclusions and found that no individual state is driving the original conclusions. 2) Heterogeneity in fixed effects models means different means among categories such as states and year. Unobserved heterogeneity is simply variation/differences among cases which are not measured. When the data can be grouped by such categories, and there are also some evidences indicating heterogeneity, the OLS is not sufficient to control the effects of these unobservable factors (Colonescu 2016). However, fixed effects models can control and estimate these effects. I constructed mirror models using plm(y ~ x, data = mydata, within = "state") and found that a fixed effects model do not alter the overarching conclusions even when absorbing the effects particular to each state (Torres-Reyna 2010). Both methods resulted in successful measures of robustness confirming HHH's original quantitative findings, if not the exact theoretical claim.

In addition to exploring the robustness of HHH's findings, I built a new model using the original datasets to explore the association between economic indicators and changes in Republican voters. I constructed a series of models that explain shifts in GOP share of voters in terms of changes in hispanic proportion, changes in unemployment, and proportion change of poor to consider the economic influences on Republican voters share shifts respectively and in combination. In addition, I construct a model to examine how the interaction of change in unemployment and change in Hispanic proportion affect GOP vote share in each time period. I also construct a model using only changes in unemployment and proportion change of poor as explanatory

variables to GOP share in these intervals. The results show that unemployment may have an even stronger effect on GOP share of voters between 2011-2016, indicating an interesting trend in the way voters appear to be penalizing candidates in general elections.

Through a brief overview of the relevant literature and a visual presentation of the data, I introduce the scope of this project. I then conduct 3 robustness test to examine the validity and reliability of HHH's findings and later expand their analysis through a new model exploring economic indicators' and their relation to GOP vote share in association with changes in Hispanic population proportion. I include an appendix with my R-based replication of the main models of the original paper.

3 Paper & Literature Review

As HHH explain in their paper, "immigration and demographic change have become highly salient in American politics, partly because of the 2016 campaign of Donald Trump" (Hilla, Hopkins, and Huberc 2019). President Trump's victory seemed to solidify the previously proposed notion that demographic changes lead to "threatened reponse" in native voters realigning voting patterns on "the basis of ethnicity, nativity, nationalism, and education" (Hilla, Hopkins, and Huberc 2019). This theory implies that as demographic changes occur, native voters shift towards more populist and outspoken anti-immigration candidates. Research of anti-immigrant and Brexit, U.K. independent party, support in the United Kingdom found that these attitudes are higher in "localities that have low immigrant shares but recent demographic changes" (Goodwin and Milazzo 2017). This trend is also true of other countries in continental Europe. In the United States, previous research with county-level data have shown that pro-GOP shifts are only associated with increases in low-skilled immigrants while increases in high-skill immigrants actually increases support for the Democratic parties (Mayda, Peri, and Steingress 2018).

Other studies at the county-level have also found an association between percentage increase in Hispanic population and shifts to the Republican Party from 2012-2016 (Enos 2017). Reny, Collingwood, and Valenzuela (2019), another study on Trump's political victory, finds that racial attitudes, and not economics, are largely associated with the shift in working-class whites' vote in 2016. However, their findings are not associated with local influx of Hispanics or demographic shifts, but rather the nationalist rethoric of the candidate (Reny, Collingwood, and Valenzuela 2019). Consequently, the theory remains inconclusive as Reny, Collingwood, and Valenzuela failed to find such a strong relationship between proportion change of Hispanics and Republican support at the local level and Newman, Shah, and Collingwood (2018) "show that the relationship between local demographic change and Trump favorability among Republicans was time-dependent" (Newman, Shah, and Collingwood 2018).

HHH combined American Community Survey (ACS) data and Census data to construct measures of demographic changes for 2000 to 2016 and 2011 to 2016. These time intervals capture "2 theoretically distinct characterizations of immigrant threat" First, HHH noted the potential for citizens' anxiety caused by "cumulative, longterm changes in local demographics" and activated by Trump's candidacy. HHH also noted the theoretical pathway where "more recent changes are most salient for individuals' perceptions of their local communities," which would result in threatened response (Hilla, Hopkins, and Huberc 2019). Using a precinct-level dataset of election results and demographic measures for almost 32,000 precincts in the states of Florida, Georgia, Michigan, Nevada, Ohio, Pennsylvania, and Washington, HHH find that the influxes in Hispanic and foreign born groups did not influence voting behavior in favor of Trump, but rather (in a slight way) benefited his opponent in those particular areas.

HHH employ OLS regression analyses with varying explanatory variable(s) specifications and measures of 'demographic change' resulting in 8 main regression models as well as loess lines that visually and mathematically demonstrate the relevant results. They study change in proportion of Hispanics and proportion change of Hispanic proportions concluding that in places with demographic shifts, Trump did not benefit, but, in fact, Clinton did. In other words, local demographic changes are not, on their own, increasing support for anti-immigration candidates. HHH argue that this means the precincts in question are not engaging in the previously studied "threatened response" associated with voting behavior in light of immigration influxes. The authors acknowledge that "despite its disparate local impacts, immigration may be a symbolic,

nationalized issue whose effects, do not depend on local experiences" (Hilla, Hopkins, and Huberc 2019). However, the actual connection has yet to be proven empirically and it is tough to address it given several exogenous factors influencing voting patterns. Some of these factors include, but are not limited to, greater exposure to international trade and declining economic prospects for the less educated. Despite these unexplored conditions, the authors explain that 'positive intergroup contact' could be responsible for the seemingly 'supportive' voting patterns at low levels of aggregation (locally). This idea is partially supported by Enos (2014), whose study shows how individuals with long(er) exposures to minority groups, tend to have less exclusionary attitudes than those who are exposed to them only briefly or those who have never been exposed at all (Enos 2014). Notably, the authors discuss the research on the different ways in which influx of immigrants affect voters' response, but the variables used in this analysis mainly focus on influx of Hispanics, who may or may not be immigrants themselves.

4 Replication

I was able to successfully translate and replicate the main analysis of the original paper despite minor deviances that did not affect the overall conclusions of the study. Since the original analysis was done in Stata, this project required the translation of the code and a comparative analysis. A full replication of Table 1 and Figure 1 using the most approximate R tools of the original paper can be found in the appendix.

5 Robustness Check #1: Subsetting the Data

One way to test for robustness is to examine the ways in which different states affect the overall trends. Notably, if a subset of the data has largely skewed results, the original findings are not invalidated given the diminished statistical significance of the subset, but the results' predictive applicability and generizability can be questioned. For this project, I decided to run the main 8 original models on a smaller subset of the data - the precincts in the state of Florida. Examining the single state allowed me to zoom in and see how these associations look like in a state that is increasingly known as a swing state in U.S. elections.

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Table 1: Change in Republican vote share 2012 to 2016 and change in Hispanic population, various time intervals in FL

	Dependent variable:							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Change in Prop. Hispanic, 2011 to 2016	−0.039**	0.035***	0.068***					
	(0.017)	(0.011)	(0.010)					
Prop. Change in Prop. Hispanic, 2011 to 2016				−0.003***				
				(0.001)				
Prop. Hispanic 2011		−0.098***	0.121***	0.121***				
		(0.003)	(0.003)	(0.003)				
Prop. Change in Prop. Hispanic, 2000 to 2016								0.002
								(0.001)
Change in Prop. Hispanic, 2000 to 2016					−0.017	0.025***	−0.046***	
					(0.011)	(0.008)	(0.008)	
Prop. Hispanic 2000						−0.105***	0.113***	0.114***
						(0.004)	(0.004)	(0.004)
Constant	−0.007***	0.004	0.110***	0.108***	−0.006***	0.042***	0.106***	0.098***
	(0.001)	(0.005)	(0.006)	(0.006)	(0.001)	(0.003)	(0.004)	(0.004)
Observations	4,938	4,938	4,938	4,923	4,938	4,938	4,938	4,938
R^2	0.001	0.552	0.619	0.617	0.0005	0.524	0.583	0.581
Adjusted R^2	0.001	0.551	0.618	0.616	0.0003	0.522	0.582	0.579
Note:								*p<0.1; **p<0.05; ***p<0.01

Despite the lack of statistical significance across many of the coefficients in Table 1, comparing these models' output and their significance to those of the original data models solidify HHH's central finding as even a small subset of the data seems to confirm their overarching conclusion that demographic shifts do not lead to increased GOP share of votes, but rather the opposite. I think the question can now become whether or not the influx of hispanics can be interpreted as an influx of immigrants (which is a big discussion in the theoretical part of the original paper) or if it simply refers to U.S. born Hispanics, which have been found in previous research to vote in favor of Democratic candidates. In the main eight regressions explored in the study, foreign born population is not included as an explanatory variable control, so this change in Hispanic proportion can be assumed to include any Hispanic in America. Notably, the appendix of the original paper contains a table that explores the effect of foreign born changes on GOP vote share. Perhaps the relationships uncovered through those models can help clarify the more specific claim discussed in the literature. Unfortunately, I was unable to gain access to the appendix for this project. Overall, these models serve as a robustness check to HHH's findings and provide some insight into the consequences of slicing the data in different ways and the potential effect individual states may be having on the data as a whole, which is further explored in the next set of models.

Another similar, but more extensive way to test for robustness, is to build a series of models in which a

different state is substracted from the sample each time. This allows to observe whether the overall trend is largely skewed by any individual state.

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Table 2: Change in Republican vote share 2012 to 2016 and change in Hispanic population

	Dependent variable:						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Change in Prop. Hispanic, 2011 to 2016	-0.086^{***}	-0.072^{***}	-0.063^{***}	-0.066^{***}	-0.055^{***}	-0.068^{***}	-0.068^{***}
	(0.008)	(0.006)	(0.006)	(0.007)	(0.006)	(0.007)	(0.007)
Prop. Hispanic 2011	-0.188^{***}	-0.132^{***}	-0.130^{***}	-0.133^{***}	-0.127^{***}	-0.132^{***}	-0.133^{***}
	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Constant	0.179^{***}	0.159^{***}	0.151^{***}	0.165^{***}	0.137^{***}	0.176^{***}	0.168^{***}
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Observations	27,373	30,892	28,991	30,846	25,425	23,854	26,485
R^2	0.662	0.631	0.633	0.645	0.608	0.667	0.661
Adjusted R^2	0.662	0.631	0.633	0.645	0.608	0.667	0.661
Note:							*p<0.1; **p<0.05; ***p<0.01

The coefficients of these models (each of which excludes a different state) consistently support HHH's findings and conclude that the results are not driven by any single state.

6 Robutness Check #2: Fixed Effects Model

In statistics, a model that has fixed parameters or non-random quantities is called fixed effects model. In general, based on some observed factors, data can be divided into groups. The group means could be assumed as constant or non-constant across groups. And in a fixed effects model, just as its name implies, each group mean is a specifically fixed quantity. Furthermore, the assumption of fixed effect is that the group-specific effects are correlated with the independent variables. Heterogeneity in fixed effects models means different means among categories such as states. Unobserved heterogeneity is simply variation/differences among cases which are not measured. When the data can be grouped by such categories, and there are also some evidences indicating heterogeneity, the OLS is not sufficient to control the effects of these unobservable factors. However, fixed effects models can control and estimate these effects. The plm fixed effects model essentially captures any and all systematic differences across precincts that are state-invariant.

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Table 3 shows a lack of statistical significance for Models #1 and #5 compared to the original and replicated models, which show statistical significance across all 8 models. Notably, the overall effect of Hispanic proportion change on Republican vote share appears weak and unreliable when accounting for the systematic differences across precincts (the fixed effects model). However, the direct effect seems clearer as more explanatory variables are added. These coefficients are similar in sign and magnitude to the original findings and support HHH's findings.

Table 3: Change in Republican vote share 2012 to 2016 and change in Hispanic population, various time intervals, fixed effects by State

	Dependent variable:							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Change in Prop. Hispanic, 2011 to 2016	−0.007	−0.050***	−0.072***					
	(0.010)	(0.006)	(0.006)					
Prop. Change in Prop. Hispanic, 2011 to 2016				−0.004***				
				(0.0004)				
Prop. Hispanic 2011		−0.101***	−0.128***	−0.128***				
		(0.002)	(0.002)	(0.002)				
Prop. Change in Prop. Hispanic, 2000 to 2016								−0.006***
								(0.0004)
Change in Prop. Hispanic, 2000 to 2016					0.003	−0.043***	−0.105***	
					(0.007)	(0.005)	(0.005)	
Prop. Hispanic 2000						−0.110***	−0.123***	−0.140***
						(0.003)	(0.002)	(0.002)
Observations	32,929	32,311	32,311	31,368	32,913	32,911	32,911	32,909
R^2	0.00001	0.502	0.560	0.558	0.00001	0.504	0.553	0.550
Adjusted R^2	−0.0002	0.502	0.560	0.557	−0.0002	0.504	0.553	0.550
Note:								*p<0.1; **p<0.05; ***p<0.01

7 A New Model: Economic Indicators & Hispanic Population Change

This model isolates economic indicators to explore their effect on republican vote share as well as its association to hispanic proportion changes.

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Table 4 explores the association between economic indicators and changes in Republican voters between 2011 and 2016. The first model indicates that changes in unemployment between 2011 and 2016 have a stronger negative effect on the change of Republican vote share (positive values indicate pro-Republican shifts) than increases in Hispanic proportion change during this time period. The magnitude is significantly greater and both values hold statistical significance. In model 2, we observe the interaction effect between Hispanic change and unemployment change is actually positive suggesting that if there is both an influx of Hispanics and a spike in unemployment, then the Republican vote share would be positively impacted. Notably, this value is not statistically significant due to its large standard error and requires further testing. Model 3 indicates that changes in proportion of poor is associated with positive change in GOP votes share, a value that is small, but statistically significant. The interaction between change in proportion of Hispanics and change in proportion of poor resulted in a miniscule positive coefficient without statiscal significance, which may indicate Republican favor, but requires further analysis. The last model shows the effect of each of these explanatory variables when controlling for the others indicating that changes in unemployment has, in fact, a much stronger influence than even Hispanic influx over the 2012-2016 period.

8 Conclusion

HHH argue that demographic shifts did not benefit Trump at the precinct level during the 2016 election, but rather his opponent. The authors find consistent evidence that hispanic influx led to decreased republican

Table 4: Change in Republican vote share 2012 to 2016 and change in Economic Indicators and Hispanic population, various time intervals

	Dependent variable:				
	(1)	(2)	(3)	(4)	(5)
Change in Prop. Hispanic, 2011 to 2016	-0.036^{***}	-0.031^{***}	-0.045^{***}	-0.045^{***}	-0.043^{***}
	(0.010)	(0.011)	(0.010)	(0.010)	(0.010)
Change in Prop. Unemployed, 2011 to 2016	-0.269^{***}	-0.274^{***}			-0.296^{***}
	(0.016)	(0.016)			(0.016)
Interaction: Chg Prop. Hisp 11-16 and Chg Prop. Unemp. 11-16		0.415			
		(0.336)			
Change in Prop. Poor, 2011 to 2016			0.075^{***}	0.074^{***}	0.095^{***}
			(0.008)	(0.008)	(0.008)
Interaction: Chg Prop. Hisp 11-16 and Chg Prop. Poor 11-16				0.014	
				(0.166)	
Constant	-0.0004	-0.001	0.002^{***}	0.002^{***}	-0.002^{***}
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Observations	32,929	32,929	32,925	32,925	32,925
R^2	0.010	0.010	0.003	0.003	0.014
Adjusted R^2	0.009	0.009	0.003	0.003	0.014
Note:					*p<0.1; **p<0.05; ***p<0.01

vote share. My replication was successful despite the deviances inherent to a translation of the original models to R. The three robustness tests further confirmed HHH's findings, which allowed me to explore a new model using economic indicators as explanatory variables to GOP vote share. The results are intriguing indicating a stronger relationship between increased unemployment and GOP vote share than any of the other variables studied. This finding suggests opportunities for further studies exploring the mechanisms through which unemployment affects the outcome.

9 Appendix

9.0.0.1 Replication of Table 1: Table 1 presents multiple least-squares regression estimates of how changes in Hispanic populations at different time intervals correlate with increases in Republican precinct-level vote share between 2012 and 2016.

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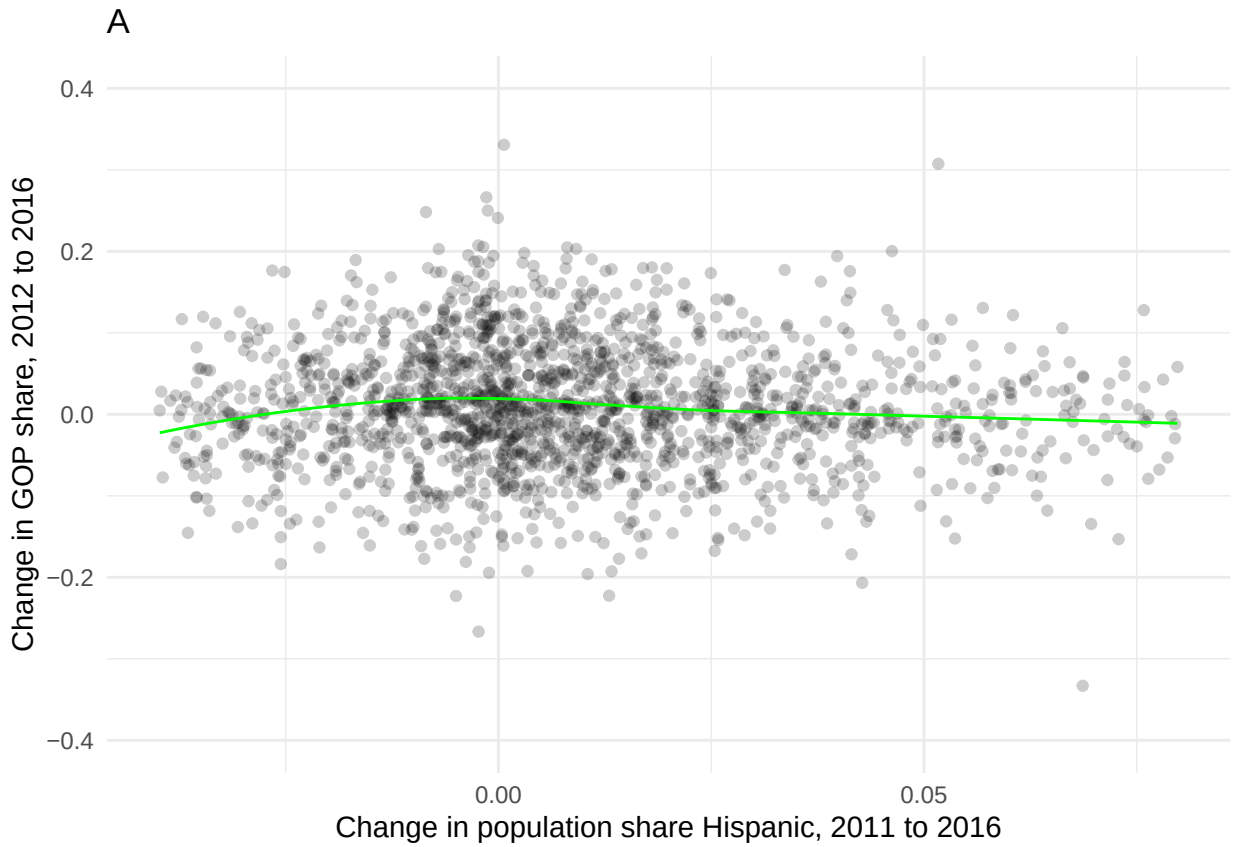
Table 5: Table 1. Change in Republican vote share 2012 to 2016 and change in Hispanic population, various time intervals

	Dependent variable:							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Change in Prop. Hispanic, 2011 to 2016	−0.031***	−0.045***	−0.065***					
	(0.010)	(0.007)	(0.006)					
Prop. Change in Prop. Hispanic, 2011 to 2016				−0.004***				
				(0.0005)				
Prop. Hispanic 2011		−0.110***	−0.132***	−0.133***				
		(0.002)	(0.002)	(0.002)				
Prop. Change in Prop. Hispanic, 2000 to 2016								−0.005***
								(0.001)
Change in Prop. Hispanic, 2000 to 2016					−0.056***	−0.044***	−0.089***	
					(0.007)	(0.005)	(0.005)	
Prop. Hispanic 2000						−0.122***	−0.132***	−0.147***
						(0.003)	(0.002)	(0.002)
Constant	−0.00002	0.055***	0.156***	0.156***	0.002***	0.065***	0.132***	0.129***
	(0.0004)	(0.002)	(0.003)	(0.003)	(0.0005)	(0.001)	(0.002)	(0.002)
Observations	28,934	28,934	28,934	28,934	28,934	28,934	28,934	28,934
R^2	0.0003	0.587	0.636	0.635	0.002	0.571	0.614	0.612
Adjusted R^2	0.0003	0.586	0.636	0.635	0.002	0.571	0.614	0.611
Note:								*p<0.1; **p<0.05; ***p<0.01

9.0.1 Figure 1

Figure 1 (A, B, C, & D) examine(s) how changes in Hispanic populations correlate with increases in Republican precinct-level vote share between 2012 and 2016. The figure shows change in the Republican share of the 2-party vote from 2012 to 2016 (positive values indicate pro-Republican shifts) against 4 different measures of change in the Hispanic population on the x axis. The 1st frame (A) measures changing population as the change in the Hispanic proportion of the overall population from 2011 to 2016, the 2nd (B) as the same change from 2000 to 2016, and the 3rd (C) and 4th (D) as proportional changes in the Hispanic population for each period.

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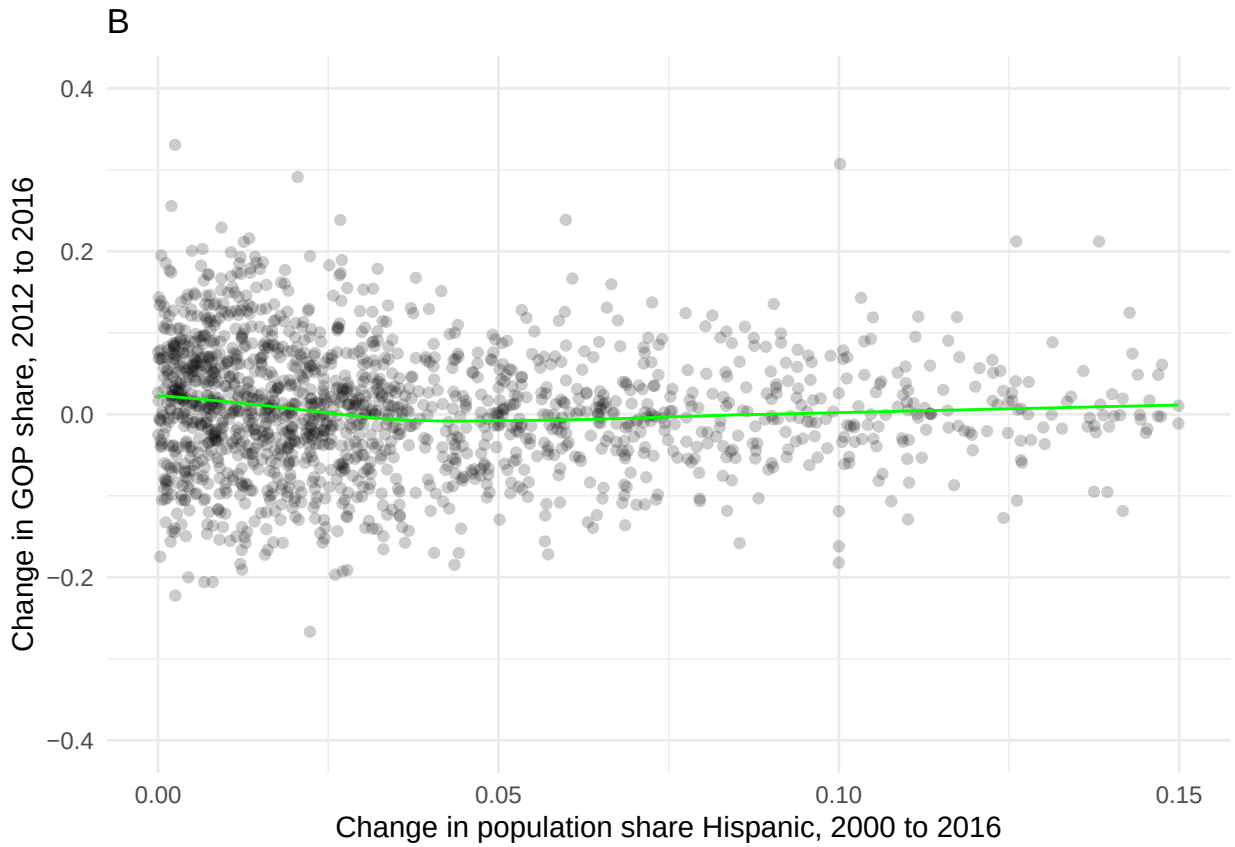


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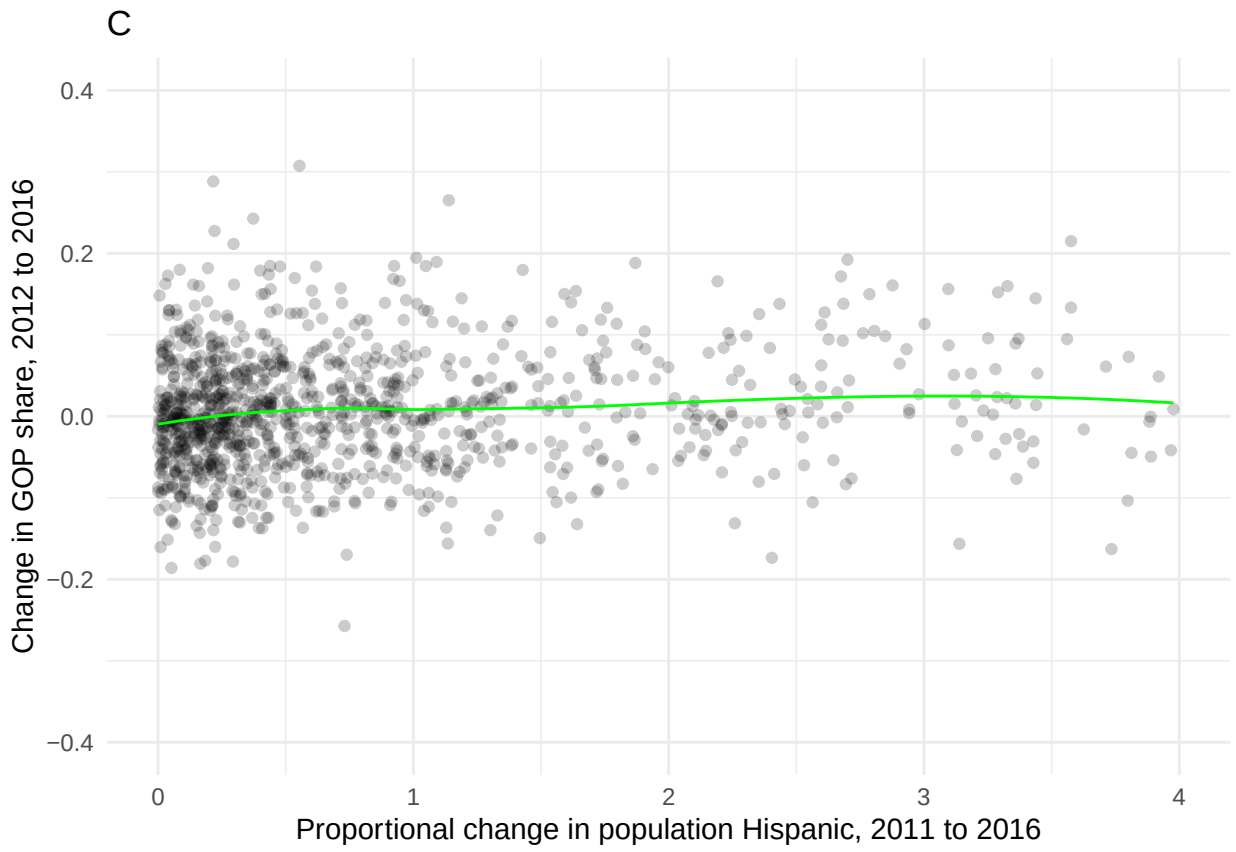


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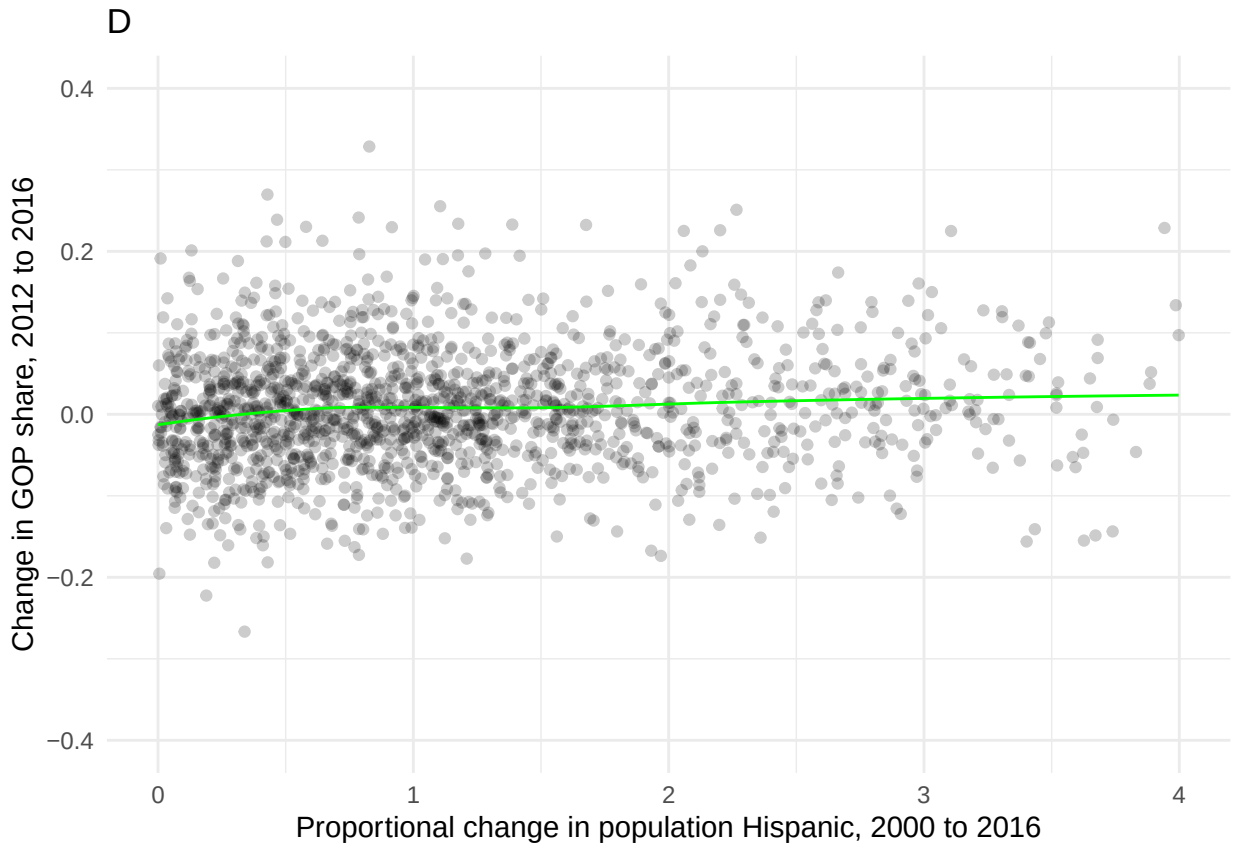

The figure shows a negative relationship between increasing Hispanic populations and heightened Republican support. This association holds for either the between-election time period of 2011 to 2016 or the longer time period of 2000 to 2016. Proportional changes in the 3rd and 4th frames both show a flat relationship between proportional change and change in Republican support.

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