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# Political and Sociodemographic Determinants of Covid-19 Vaccination in Florida: A Spatial Analysis<sup>\*</sup>

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**Abstract:** This paper explores the determinants of Covid-19 vaccination in Florida, focusing on demographic, economic, and political preferences. Using data from vaccine intake for Floridians from January to June 2021, we explore the spatial variation in Covid-19 vaccination patterns and regional characteristics to analyze the main features associated with vaccine intake. We use spatial econometric techniques to verify the spatial autocorrelation between vaccination rates and estimate models that can account for spillover effects between counties. Our data allow us to explore differential effects for vaccination patterns across population subgroups according to gender, race and ethnicity, and age. Our results show that political preference has the largest effect on vaccination patterns and that this effect was persistent over time. *Keywords*: Covid-19, Florida, vaccination, political preference

*JEL Codes*: R29, I12, H8

## 1. INTRODUCTION

In January 20, 2020, the United States had its first reported case of the Novel Coronavirus. Between March 13 and 15, after the World Health Organization declared SARS-CoV-2 (Covid-19) a pandemic, the United States government declared a nationwide emergency, issued travel bans on non-U.S. citizens, and states began to implement shutdowns to contain the spread of the virus.<sup>1</sup> While states like Florida nearly fully reopened by September 2020, other states' shutdowns lasted until March 2021, and only in May 2023 that the United States government would officially end the Covid-19 emergency state. The pandemic created

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<sup>&</sup>lt;sup>1</sup>https://www.cdc.gov/museum/timeline/covid19.html

significant economic and social disruptions throughout the world (Deb et al., 2022; Brodeur et al., 2021), many of which we are still recovering from.

Given the scale and nature of the Covid-19 pandemic, many policies were implemented to mitigate its health, social, and economic effects (Mahmoudi, 2023). In this study, we focus on the Covid-19 vaccination policy. The roll-out of the Covid-19 vaccination was projected to contain the spread of the virus, while offering relief from the economic recession in 2020. However, many people were hesitant to take the Covid-19 vaccine. Hesitancy varied based on several factors. There is a vast literature on the determinants of vaccination, however, little has been discussed on the effects of politics on vaccination, which has been especially relevant for the Covid-19 pandemic (Bolsen and Palm, 2022; Ugarte et al., 2021; Young et al., 2022). Therefore, we focus on the Covid-19 vaccination policy and outcomes in Florida. Florida is an interesting case study given its political landscape and data availability. On the one hand, the state is considered a "swing" state in that both Democratic and Republican parties have somewhat similar level of support. One the other hand, the state opted for a less strict central response to the Covid-19 pandemic.

The literature and theory suggest the existence of potential spatial spillover patterns in the vaccination rate given its determinants (Cunha et al., 2022; Bourdin et al., 2023; Kang et al., 2023). Hence, first we explore the spatial patterns of the cumulative vaccination rate in Florida by June 1st, when every adult in Florida would have been eligible to have completed its vaccination schedule. Then, look into how the different determinants - economic, demographic, and political - affected the vaccination rate in Florida by estimating an Ordinary Least Squares (OLS), a Spatial Lag of X (SLX), a Spatial Durbin (SDM), and a Spatial Durbin Error (SDEM) models. Next we break our analysis by different demographic groups (gender, race, ethnicity, and age) and by timeline (January through June).

So far, most studies have focused on country level or state level variation (Bollyky et al., 2023a; Uzuegbunam et al., 2023; Liu and Li, 2021; Maloney and Taskin, 2020; Bourdin et al., 2023). In this paper, we take a step further and look at vaccination rates and its determinants focusing across Florida counties. We use data from the Florida Department of Health (FDOH) which provided daily vaccination information for each Florida county for several sub-population groups including race, ethnicity and age. Data on demographic and economic indicators come from the American Community Survey (ACS), and we rely on the Data and Lab (2017) data for the voting outcomes for presidential elections by county.

Our results suggest that political preference, gender, age, and education help explain vaccination rate. In particular we find that areas with larger share women and with larger share of votes on Trump had a negative association with vaccination rates, but older regions and those with higher average educational attainment were positively correlated with vaccination rate. These effects seem to increase with time for political preference and for median age, but are not consistent for educations and gender. Indirect effects are not statistically significant for the cumulative vaccination rates, but when breaking down by timing of vaccine intake, the most consistent spillover effects are from race and political preferences. While neighboring counties with larger white population are associated with less vaccinations, neighboring counties with higher Trump vote are associated with higher vaccination rates.

Our contribution is three-fold. First, we contribute to the literature by incorporating a spatial component to our analysis. This is important on aggregate analysis like ours to account for potential spillovers effects. Second, our study focuses on the state of Florida. We are able to conduct our analysis on a finer geographic level and analyze an important swingstate. This allows us to further explore the role of political preference on a topic that was much influenced by political discourse. Lastly, we are able to explore the differential effects of sociodemographics and political preference on the vaccination rate of different groups and over time.

The remainder of the paper is as follows: section 2 first discusses the determinants of vaccinations in general and associated with Covid-19, then presents a timeline of the vaccination in Florida; section 3 provides the data and the empirical model used in the analysis; section 4 focuses on the results and section 5 concludes.

#### 2. BACKGROUND

#### 2.1. Determinants of Vaccine Intake

Many studies have examined how the impact of Covid-19 has been reduced through the actions of individuals as well as policy implementations. When determining the effects of non-pharmaceutical intervention, Maloney and Taskin (2020) found that the majority of social distancing measures were put in place voluntarily and were driven by the number of Covid-19 cases and awareness of risk. While these restrictions have been implemented to control the spread of the virus, it resulted in significant economic losses. Deb et al. (2022) examined how increases in vaccinations affected economic activity measured by nitrogen dioxide emissions, carbon monoxide emissions, and Google mobility indices. Using county-month panel data the study found marginal economic benefits associated with larger vaccination rates and evidence of spillover effects.

Although the implementation of non-pharmaceutical intervention as well as vaccinations aimed to benefit the economy, some people were hesitant to adapt to the mandated and proposed guidelines. This hesitancy differed between demographic and economic factors. Race, gender, income, education, political preference as well as many other factors have been found to contribute to a persons' willingness and acceptance of Covid-19 vaccinations. Studies focusing on demographic and economic factors (Endrich et al., 2009; Doornekamp et al., 2020; Burger et al., 2021; Rifai et al., 2021; Staples et al., 2021) have found that African Americans are (overwhelmingly) less likely to vaccinate and have higher vaccine hesitancy. In analyzing regional variations, Rifai et al. (2021) showed that Florida was one of the states where racial influenza vaccination disparities were the largest. These studies find no consensus regarding vaccination rate and hesitancy across gender but find age positively correlates with vaccination uptake.

Similar to gender, there are mixed results regarding the direction of the correlation between education level and income, and vaccination uptake or hesitancy. Additionally, there is documented difference between initiation rates and series completion across groups. Looking at the human papillomavirus (HPV) vaccine, for instance, Staples et al. (2021) find that regions that are poorer and have higher unemployment rates also had higher series completion rates compared to their richer counterparts, but lower initiation rates.

However, although there are some similar patterns of vaccine intake and hesitancy for

sub-population groups, the disease itself also played some role on the uptake and hesitancy (Doornekamp et al., 2020). Despite the novelty of the Covid-19 and its vaccine, a number of studies have already analyzed how social, demographic and economic factors influencing both the hesitancy and the intake of the Covid-19 vaccine. For the most part, the results are in line with the previous literature on other types of vaccine (Schwarzinger et al., 2021; Malik et al., 2020; Kadoya et al., 2021; Viswanath et al., 2021; Beleche et al., 2021).

One factor that has been extremely relevant for the acceptance of the Covid-19 vaccine is political preference. In the United States there has been some hesitancy towards policies aimed at slowing down the spread of Covid-19 such as wearing masks and especially vaccinations. Dowd-Arrow et al. (2023) examined the practices of Democrats and Republicans and found that Democrats often reported engaging in less risky behavior during the pandemic and were more likely to be vaccinated. It was also reported that older age strengthened a person's choices based on their party affiliation.

The polarized reaction to Covid-19 vaccinations between Democrats and Republicans resulted from differing views of the virus itself. The Covid-19 virus discussion experienced high levels of politicization where political views were integrated into the media coverage during the pandemic (Bolsen and Palm, 2022). Social media coverage of the virus added to the politicization by spreading false claims, conspiracy theories, and pseudo-scientific health therapies (Bolsen and Palm, 2022).

The behaviors of Democrats and Republicans can be seen in the effects Covid-19 had on these two groups. During the presidential election in 2020, majority political preference by county was significantly associated with Covid-19 infection rate (Bernet, 2022). Similar outcomes can be seen in the mortality rate once vaccines were released. Wallace et al. (2023) found that once vaccinations were available to all adults, excess mortality was much higher among Republican voters than among Democrat voters.

Table 1 provides a summary of the literature regarding the different determinants considered in this study, the findings for general vaccines and for Covid-19 vaccines and the references.

#### 2.2. Covid-19 Vaccination Timeline in Florida

In this subsection we focus on the timeline of the Covid-19 vaccines in Florida.<sup>2</sup> Distribution of Covid-19 vaccinations in the state of Florida began on December 14, 2020 and every adult (age 18 and over) was eligible to initiate its vaccination schedule on April 5, 2021. Table 2 provides the different events that took place in the state regarding vaccination eligibility, and other associated numbers.

While there were different tones regarding the efficacy of the Covid-19 restriction measures and vaccines, nearly all states did impose restrictions, especially between March and June 2020. The main difference among states' response started in November 2020 with the Delta variant of Covid-19 virus. Some states reinstated mandates, and others like Florida, did not reimpose them. According to Bollyky et al. (2023b), using data from Bollyky et al.

 $<sup>^2{\</sup>rm For}$  a complete timeline of the Covid-19 pandemic and vaccines in the United States please see https: //www.cdc.gov/museum/timeline/covid19.html.

Determi	- Conoral Vaccinos	Covid-19 Vac-	Beferences	Variables
nants	General vaccines	cine	Itelefences	variables
nants Gender Race & Ethnicity	Most studies indi- cated males had a higher correlation with being vacci- nated or vaccine acceptance than females.	cine Mixed results show that men are more likely to have a higher level of vaccine accep- tance compared to women, but this difference can fade over time Higher hesitancy rates for African	Doornekamp et al. (2020), Endrich et al. (2009), Staples et al. (2021), Burger et al. (2021) Schwarzinger et al. (2021), Malik et al. (2020), Kadoya et al. (2021) Burger et al. (2021), Rifai at al. (2021) Staples et al.	Percent Fe- male
Etimicity	more hesitant and less likely to vaccinate than Whites.	Americans com- pared to Whites, gap in rates be- tween the two groups falls over time.	(2021), Staples et al. (2021) Malik et al. (2020), Viswanath et al. (2021), Beleche et al. (2021)	Percent Hispanic
Age	Majority of results indicate higher acceptance and uptake rates among older populations, but few showed higher rates for younger adults.	Mixed results show older adults are less likely to be hesi- tant, but correla- tion varies by age- group and a non- linear relationship.	Rifai et al. (2021), Endrich et al. (2009), Toll and Li (2021) Kadoya et al. (2021), Ma- lik et al. (2020), Schwarzinger et al. (2021)	Median Age
Educational Level	Mixed results show that the rela- tionship between education level and vaccination uptake/acceptance depends on certain factors.	A higher level of education consis- tently correlated with higher vaccine acceptance rates.	Burger et al. (2021), Rifai et al. (2021), Toll and Li (2021), Endrich et al. (2009), Doornekamp et al. (2020) Nikolovski et al. (2021), Viswanath et al. (2021), Malik et al. (2020)	Percent Edu- cation (some college and higher)
Economic Indicators	Effects of income, poverty, unemploy- ment, and other economic measures on vaccination uptake/acceptance can vary depending on certain factors.	Mixed results for effects of employ- ment on vaccina- tions, but consis- tently positive ef- fects were found for higher income.	Endrich et al. (2009), Staples et al. (2021), Rifai et al. (2021) Malik et al. (2020), Viswanath et al. (2021), Kadoya et al. (2021), Beleche et al. (2021)	Percent Inter- net
Political Indicators	Results found that Republicans are less likely to receive vaccines than Democrats specifically during times of outbreaks.	Differing views of the virus resulted in polarized reac- tions to vaccina- tions with Repub- licans being more hesitant to vacci- nate.	Dowd-Arrow et al. (2023), Bolsen and Palm (2022), Ber- net (2022), Wallace et al. (2023), Suryadevara et al. (2019), Mesch and Schwirian (2015), Baumgaertner et al. (2018)	Percent Trump Vote

 Table 1: Summary of Literature

	Table 2: I folida Covid 15 Vaccine Timen	
Date	Event	Cumulative Deaths (reporting week)
December 14, 2020	First vaccines distributed in Florida. Vaccines were made available to health care workers and people in nursing homes.	20,128 (December 19)
February 12, 2021	Vaccinations made available at additional sites (pharmacies and supermarkets).	28,148 (February 13)
March 3, 2021	Executive order EO 21-47 goes into effect. The executive order expands eligibility to in- clude: long-term care facility residents and staff; persons 65 years of age and older; per- sons under 65 years old deemed medically vul- nerable by a physician (form required) and may only be administered by physician, ad- vanced practice registered nurse, or licensed pharmacist; health care personnel with di- rect patient contact; K-12 school employees 50 years of age and older; sworn law enforce- ment officers 50 years of age and older; and functional scheme and a labor.	29,909 (March 6)
March 15, 2021	EO 21-62 goes into effect. The executive order expanded eligibility to include all individuals over the age of 60, as well as individuals spec- ified in EO 21-47.	30,693 (March 20)
March 22, 2021	EO 21-67 goes into effect. The executive order expanded eligibility to include all individuals over the age of 50.	31,035 (March 27)
March 29, 2021	EO 21-79 goes into effect. The executive order expanded eligibility to include all individuals over the age of 40.	31,391 (April 3)
April 5, 2021	EO 21-79 expanded eligibility to include all individuals over the age of 18.	31,684 (April 10)
April 13, 2021	Distribution of Johnson & Johnson vaccine is paused due to safety reasons.	32,011 (April 17)
April 26, 2021	Distribution of Johnson & Johnson vaccine is reinitiated.	32,721 (May 1)

Table 2: Florida Covid-19 Vaccine Timeline

Timeline obtained at https://www.floridahealth.gov/diseases-and-conditions/respiratory-illness/ COVID-19/news.html and cumulative deaths at https://covid.cdc.gov/covid-data-tracker. By January 1, 2022 there were 59,655 total deaths in the state, by January 7, 2023 there were 76,370 deaths, and by November 18, 2023 there were 81,254 deaths in Florida. (2023a), Florida adopted more mandates than most other states early in the pandemic, but once lifted they were not reinstated. Also, in regards to the vaccine, even though there was a skeptic tone from the Florida government vaccines were available in the state in a similar timeline to other states in the country.

#### 3. DATA AND EMPIRICAL APPROACH

#### 3.1. Data

The vaccination data used comes from the daily reports generated by the state's Department of Health. The data spans from January 31 to June 1, encompassing a time frame during which any eligible individual in Florida could have completed the full vaccination schedule. The county-level data provides cumulative totals for both the first dose and the completed vaccination series. Individuals are singularly counted, with the completion of the vaccination series recorded once they receive their second dose or the initial dose of the Johnson & Johnson vaccine. Demographic breakdowns, including age, race, and gender, further delineate vaccination totals. Notably, out-of-state vaccinations are acknowledged in the data, but individuals who traveled from outside of Florida for vaccination are not considered in the analysis.

Demographic and economic information for counties comes from the 2019 5-year American Community Survey estimates. Key variables of interest include median age, educational attainment, racial and ethnic distribution within each county, and metrics related to household internet and computer access. Additionally, we use data from the Florida Department of State's Division of Election for the 2020 General Election to capture political preferences at the county level. For our analysis we use the share of Donald Trump votes in the 2020 election, excluding state or Federal Congressional election results from the analysis. Hence, we are able to explore the nexus between vaccination rates, demographic characteristics, and political dynamics across Florida counties.

Table 3 shows the descriptive statistics for all Florida counties. The average vaccination rates across counties in Florida increased significantly from January 31st (8.4%) to June 1st (40.2%). For both months, females consistently had higher vaccination rates than males and remained above the total vaccination average. Consistent with related literature, there was a disparity in vaccination rates between white and black individuals. While 35% of the white population was vaccinated by June 1st, the vaccination rate for the black population was only 22.4\%. Additionally, those who were ages 65 and up had the highest vaccination rates (95.7\% as of June 1st) compared to younger eligible individuals.

#### 3.2. Empirical Model

The theoretical relationship between education and health investments and behaviors is explained by the Grossman model (Bhattacharya et al., 2014). This model explains that education affects the use of healthcare goods and services by increasing their marginal productivity. Simply educated individuals may follow a care plan and comprehend it (Laporte, 2020). Furthermore, more educated individuals are more prone to take vaccinations to

Table 3: Descriptive Statistics					
	Mean	SD	Min	Median	Max
Monthly Vaccination Rates					
January 1st Rates	0.86	0.57	0.07	0.78	3.30
February 1st Rates	8.52	2.31	4.45	8.11	15.24
March 1st Rates	14.71	4.80	7.33	13.79	30.38
April 1st Rates	25.79	9.06	12.54	24.70	65.42
May 1st Rates	36.20	10.07	20.00	36.20	67.60
June Vaccination Rates					
June 1st Rates	40.09	11.43	21.16	40.14	69.66
Ages 25-44	27.81	11.46	12.15	26.11	55.70
Ages 45-64	49.07	12.71	24.79	48.96	79.14
Ages 65 and up	70.24	10.95	38.60	71.20	95.70
Female	43.06	12.11	22.71	43.61	76.92
Male	37.19	10.72	19.86	37.36	62.42
Hispanic	24.74	8.58	8.47	24.54	49.80
Black	22.35	5.91	2.37	22.14	36.60
White	34.97	9.63	18.93	35.16	64.98
Florida Population Statistics					
Percent female	48.66	3.74	34.79	50.51	52.57
Percent hispanic	14.38	13.08	2.60	9.70	68.50
Percent black	14.54	9.46	3.00	12.00	56.10
Percent white	78.94	9.84	39.60	80.80	92.80
Percent internet	78.14	9.03	58.10	81.50	90.90
Percent educ (some college and higher)	51.89	12.15	27.69	53.11	74.51
Percent Trump	63.36	13.57	31.40	64.60	89.10
Percent white	0.79	0.10	0.40	0.81	0.93
Percent black	0.15	0.09	0.03	0.12	0.56
Percent hispanic	0.14	0.13	0.03	0.10	0.69

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Figure 1: Vaccination rates for all population by June 1st.

achieve a better health outcome and lower the risks of Covid.

Individuals in the state of Florida were able to travel across counties to receive their immunizations, and there are strong ties between individuals across counties. Additionally, Figure 1 shows that vaccination rates follow a pattern of similar levels across neighboring counties. Therefore, to take these spatial patterns into account, we will use spatial econometrics models to explore the importance of the spillover effects in vaccination rates across counties. Following Lesage (2014), we consider three spatial models: first, the Spatial Lag of X Model (SLX) in equation (1) uses the spatial lag of the independent variables; next, the spatial Durbin Model (SDM) in equation (2) uses the spatial lag of the dependent and independent variables; last, the Spatial Durbin Error model (SDEM) in equation (3) includes a spatial lag of the independent variables and the error:

$$y_i = \alpha + X_i \beta + W X_i \delta + \epsilon_i \tag{1}$$

$$y_i = \rho W y_i + \alpha + X_i \beta + W X_i \delta + \epsilon_i \tag{2}$$

$$y_i = \theta W y_i + \alpha + X_i \beta + W X_i \delta + \epsilon_i \tag{3}$$

where  $y_i$  is the vaccination rate in county *i*, and X is a matrix containing the control

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Variables	Moran test	P-value
Panel A: Main Analysis		
June 1st Vaccination Rate	0.459	0.001
Panel B: Subgroups		
Female Vaccination Rate in June	0.417	0.001
Male Vaccination Rate in Juner	0.488	0.001
White Vaccination Rate in June	0.338	0.001
Black Vaccination Rate in June	0.076	0.129
Hispanic Vaccination Rate in June	0.258	0.002
24 to 44 Year-old Vaccination Rate in June	0.444	0.001
45 to 64 Year-old Vaccination Rate in June	0.483	0.001
65-plus Year-old Vaccination Rate in June	0.209	0.002
Panel C: Timing		
January 1st Vaccination Rate	0.087	0.100
February 1st Vaccination Rate	0.074	0.127
March 1st Vaccination Rate	0.029	0.267
April 1st Vaccination Rate	0.220	0.001
May 1st Vaccination Rate	0.309	0.001

Table 4: Moran's I index fo	r dependent variables
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variables, including demographic characteristics, economic characteristics, and political preference. W is the row-standardized spatial weight contiguity matrix of type queen. Since we rely on a queen contiguity matrix, any county with shared borders is considered a neighbor. The SLX model is a local spillover model, and allows for an easy interpretation of direct and indirect effects, such that  $\beta$  represents the direct effect of the socioeconomic characteristics and political preference and  $\delta$  represents the spillover effect of neighboring counties' demographic and economic characteristics, i.e., their indirect effect. The SDM model is a global model that allows the interaction of the local spillover effect from the independent variables and the dependent variable of neighboring units, and such interaction makes it a global model. Lastly, the SDEM model is a local model that includes the interaction of the local spillover effect from the independent variables and the spatial lag of the error term. The recent updates to the *spatialreg* package allow the estimation of the total effect as well as the inference to the model. All control variables are standardized to allow direct comparison between them (Bivand et al., 2021; Pebesma and Bivand, 2023).

#### 4. **RESULTS**

#### 4.1. Spatial Patterns of Covid-19 Vaccination

First, we look into the spatial patterns of Covid-19 vaccination in Florida (see Figure 1). We break this analysis in two parts. Table 4 shows the Moran's index for the different vaccination rates used as dependent variables in the regression analysis. The results show a clear positive and statistically significant auto-correlation pattern for all vaccination rates except for the black population and the months of February and March. These results suggest that the use of spatial models is important and is a gap in the existing literature.



Figure 2: Local Indicators for Spatial Association (LISA) map for the Vaccination rates for all population by June 1st.

To further understand the spatial pattern of Covid-19 vaccination rates in Florida, we use Figure 1 and Figure 2, which depicts the cumulative vaccination rate in June 1st across counties in Florida (our main analysis) and the associated Local Indicators of Spatial Association (LISA) maps. These results show a clear divide in Florida regarding vaccination rate. While the North and Center-South parts of the state have lower vaccination rates, the South and the Center-North parts of the state have higher vaccination rates. The LISA map corroborates the observed pattern in Figure 1 and show several clusters in the state. In the North-Northwest we see a couple of low-low clusters with some bordering high-low counties, while in the Center and South we see some high-high clusters.

#### 4.2. Determinants of Covid-19 Vaccination

Before our regression analysis, we conduct the Lagrange Multipliers tests (Table 5) to gauge which spatial specification is better suited for our analysis. The results are inconclusive. Theory suggests that social and economic phenomena are local by nature (Lesage, 2014). Thus, we estimate a traditional OLS, and also three other spatial specifications: SLX, SDM and SDEM. The SLX and SDEM are local spillover models and the SDM is a global spillover model. Given the lack of support for the Lag or Error model, our preferred specification is the SLX.<sup>3</sup>

<sup>&</sup>lt;sup>3</sup>One concern with spatial models is the omission of existing out-of-state neighbors that are omitted from the analysis. Appendix A presents the analysis including counties in Alabama and Georgia to the analysis, and the results remain similar to that of our main analysis.

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Test	Stat	p-value
LM Error	0.00258	0.95949
LM Lag	0.26633	0.60581
Robust LM error	0.04766	0.82719
Robust LM lag	0.31141	0.57682

 Table 5: Lagrange Multiplier Tests

Our main results are presented in Table 6 with all estimated models for the cumulative vaccination rate by June 1st. The results across all specifications are similar in magnitude, sign and statistical significance, hence we focus our analysis in the SLX. Because variables are standardized, we can compare them to determine which ones are the most important determinants (drivers) of vaccination intake in Florida. In terms of direct effect, we see that the demographic and political preference are statistically significant, while there is no evidence that access to the internet helped explain vaccination intake. In particular, we find that median age (5.920), education (5.198), percent of Black (4.928), percent of White (7.044) and percent of Hispanic (4.011) populations to be positively associated with vaccinate intake. On the other hand, percent of female (-1.617) and share of Trump votes (-6.291) are negatively associated with vaccine intake. These results are consistent with those in the literature review. As for the spatially lagged variables, there is no evidence of indirect effects, except for percent of female population in the SDM and SDEM models. However these models have a negative and not statistically significant spatial coefficient.

To understand the full scope of the effect, Table 7 provides the direct, indirect and total effects along with their associated p-values for inference. Focusing on the total effects, the main determinants of vaccination intake in the state of Florida are median age, percentage of Hispanic population, and political preference. In particular, a standard deviation increase in the median age is associated with a total effect of 5.47 percentage points in vaccine intake. One standard deviation in the percentage of Hispanic population is correlated with an increase in 4.06 percentage points in the vaccination rate. Lastly, one standard deviation in the share of Trump votes is associated with a decrease of -4.65 percentage points in the vaccination rate. All of the total effects are significant and mostly driven by the direct effects.

In addition to our main regression on the total vaccination rate, we conducted two additional analyses: one for vaccination rates across different demographic subgroups to explore potential heterogeneous effects (Table 8), and one for vaccination rates in the first day of each month - January to June - to understand how these effects changed over time (Table 9). Similar to Table 7, all control variables are standardized and we show the results for the SLX model only.

*Gender*: comparing the results between male and female, similar to the main results, only direct effects are statistically significant. In addition, the results remain consistent with those in Table 6 in that median age, education and race/ethnicity are positively associated with vaccination rates, while political preferences are negatively correlated with vaccination intake. The results also show that while the direction and statistical significance is similar for vaccination rates in these groups, all variables have larger magnitude for female. Focusing on the three main variables from Table 7, median age, Hispanic population and Trump vote share are associated with 6.5, 4.1, and -5.3 percentage points change in female vaccination

	OLS	SLX	SDM	SDEM
Median age	5.718***	5.920***	5.907***	5.916***
0	(0.592)	(0.752)	(0.650)	(0.651)
Percent educ	5.275***	5.198***	5.195***	5.187***
	(1.238)	(1.521)	(1.313)	(1.319)
Percent female	-1.322*	-1.617**	-1.602**	-1.646**
	(0.684)	(0.751)	(0.652)	(0.652)
Percent black	4.151**	$4.928^{*}$	4.934**	5.063**
	(2.001)	(2.541)	(2.195)	(2.230)
Percent white	$5.917^{***}$	7.044***	$7.036^{***}$	7.191***
	(2.081)	(2.585)	(2.236)	(2.258)
Percent hispanic	$3.544^{***}$	$4.011^{***}$	4.007***	$4.052^{***}$
	(0.721)	(0.888)	(0.768)	(0.787)
Percent Trump	$-5.618^{***}$	-6.291***	$-6.264^{***}$	-6.306***
	(1.226)	(1.741)	(1.505)	(1.526)
Percent internet	0.453	0.493	0.498	0.515
	(0.887)	(0.968)	(0.836)	(0.829)
lag.Median age		-0.450	-0.177	-0.680
		(1.565)	(1.696)	(1.317)
lag.Percent educ		-1.478	-1.289	-1.640
		(3.134)	(2.826)	(2.619)
lag.Percent female		2.763	$2.734^{*}$	$2.929^{**}$
		(1.677)	(1.461)	(1.418)
lag.Percent black		-1.499	-1.189	-1.376
		(4.195)	(3.717)	(3.556)
lag.Percent white		-2.981	-2.471	-2.631
		(5.004)	(4.499)	(4.244)
lag.Percent hispanic		-0.603	-0.440	-0.734
		(1.253)	(1.251)	(1.077)
lag.Percent Trump		1.649	1.226	1.464
		(2.773)	(2.644)	(2.355)
lag.Percent internet		0.141	0.233	0.189
		(2.548)	(2.206)	(2.163)
rho			-0.057	
			(0.180)	
lambda				-0.127
				(0.184)
Num.Obs.	67	67		
R2	0.929	0.934		
R2 Adj.	0.919	0.913		
RMSE	3.03	2.92	2.92	2.91

 Table 6: Main Results

Note: \* p < 0.1, \*\* p < 0.05, \*\*\* p < 0.01. All control variables are standardized for comparison.

		-	•
Variable	Direct	Indirect	Total
Median age	$5.920 \ [0.000]$	$-0.450 \ [0.774]$	$5.469 \ [0.002]$
Percent educ	$5.198 \ [0.001]$	-1.478 [0.637]	$3.719 \ [0.289]$
Percent female	-1.617 [0.031]	$2.763 \ [0.100]$	$1.145 \ [0.516]$
Percent black	$4.928 \ [0.052]$	-1.499[0.721]	$3.429 \ [0.39]$
Percent white	$7.044 \ [0.006]$	-2.981 [0.551]	4.063 [0.412]
Percent hispanic	$4.011 \ [0.000]$	-0.603 [0.630]	$3.407 \ [0.006]$
Percent Trump	-6.291 [0.000]	$1.649 \ [0.552]$	-4.642 [0.069]
Percent internet	$0.493 \ [0.610]$	$0.141 \ [0.956]$	0.634 [0.825]

 Table 7: SLX model Impact analysis.

Note: p-values are presented in square brackets.

 Table 8: Heterogeneous Effects across Demographic Subgroups

	Female	Male	White	Black	Hispanic	Age 25-44	Age 45-64	Age $65 \mathrm{up}$
Median age	6.563***	4.763***	6.035***	0.523	-1.196			
-	(0.746)	(0.873)	(0.751)	(1.077)	(1.241)			
Percent educ	5.471***	4.484**	4.419***	-1.620	4.882**	$5.385^{***}$	$5.053^{**}$	2.485
	(1.544)	(1.808)	(1.428)	(2.046)	(2.416)	(1.647)	(1.938)	(3.173)
Percent black	$4.949^{*}$	4.290			2.874	-0.233	8.835***	$13.010^{**}$
	(2.541)	(2.975)			(4.007)	(2.642)	(3.108)	(5.089)
Percent white	6.354**	$5.792^{*}$			4.393	3.626	11.357***	17.043***
	(2.593)	(3.035)			(4.288)	(2.662)	(3.131)	(5.126)
Percent hispanic	4.124***	$3.668^{***}$	$3.470^{***}$	-0.500		$3.502^{***}$	4.420***	1.905
	(0.897)	(1.050)	(0.908)	(1.302)		(0.947)	(1.114)	(1.824)
Percent Trump	$-5.297^{***}$	-4.185**	-4.409***	-1.211	-3.611	-8.702***	-8.131***	-10.083***
	(1.634)	(1.913)	(0.883)	(1.266)	(2.897)	(1.907)	(2.242)	(3.672)
Percent internet	0.669	0.169	0.778	0.288	$-3.256^{*}$	-1.357	0.720	2.942
	(0.984)	(1.152)	(1.101)	(1.577)	(1.674)	(1.070)	(1.259)	(2.061)
lag.Median age	0.169	-0.653	-0.940	-3.832**	-0.335			
	(1.560)	(1.827)	(1.258)	(1.802)	(2.599)			
lag.Percent educ	0.870	-2.289	-3.947	-3.466	-5.274	-2.243	-0.267	9.612
	(3.158)	(3.697)	(3.435)	(4.922)	(5.130)	(3.402)	(4.002)	(6.552)
lag.Percent black	-1.580	0.504			8.265	0.259	-1.535	4.077
	(4.151)	(4.860)			(7.006)	(4.414)	(5.192)	(8.501)
lag.Percent white	-3.022	0.942			8.979	-3.859	-3.954	0.757
	(4.981)	(5.831)			(8.596)	(4.717)	(5.548)	(9.084)
lag.Percent hispanic	-0.980	0.291	-1.293	$-2.875^{*}$		-0.099	1.144	0.406
	(1.264)	(1.480)	(1.160)	(1.663)		(1.347)	(1.584)	(2.594)
lag.Percent Trump	0.991	-1.436	-0.462	-1.599	-1.362	1.507	1.901	5.759
	(2.685)	(3.143)	(1.710)	(2.450)	(3.718)	(2.833)	(3.332)	(5.456)
lag.Percent internet	-0.850	1.610	1.906	3.310	3.470	2.457	0.758	-6.263
	(2.578)	(3.018)	(2.919)	(4.183)	(4.419)	(2.862)	(3.367)	(5.512)
Percent female			-1.888**	1.754	1.784	-1.563*	-0.523	-2.644
			(0.826)	(1.184)	(1.292)	(0.825)	(0.970)	(1.589)
lag.Percent female			1.030	2.304	4.480	2.192	1.884	1.027
			(1.808)	(2.591)	(2.875)	(1.853)	(2.179)	(3.568)
Num.Obs.	67	67	67	67	67	67	67	67
R2	0.936	0.889	0.864	0.260	0.633	0.913	0.902	0.648
R2 Adj.	0.919	0.859	0.834	0.095	0.534	0.890	0.876	0.553
RMSE	3.03	3.55	3.52	5.05	5.16	3.35	3.94	6.45

Note: \* p < 0.1, \*\* p < 0.05, \*\*\* p < 0.01. All control variables are standardized for comparison. All regressions use the SLX model, our preferred specification.

	Jan	Feb	Mar	Apr	May	Jun
Median age	-0.233**	1.595***	4.013***	7.007***	6.523***	5.920***
-	(0.106)	(0.321)	(0.591)	(0.853)	(0.899)	(0.752)
Percent educ	-0.051	1.471**	$2.595^{**}$	4.064**	2.649	5.198***
	(0.214)	(0.648)	(1.195)	(1.724)	(1.818)	(1.521)
Percent female	0.033	-0.723**	-0.827	-1.015	-2.708***	$-1.617^{**}$
	(0.106)	(0.320)	(0.590)	(0.851)	(0.898)	(0.751)
Percent black	0.308	1.694	$3.660^{*}$	3.023	$5.213^{*}$	$4.928^{*}$
	(0.357)	(1.084)	(1.997)	(2.881)	(3.038)	(2.541)
Percent white	0.590	$2.245^{**}$	$4.537^{**}$	4.141	$5.813^{*}$	7.044***
	(0.363)	(1.103)	(2.031)	(2.931)	(3.091)	(2.585)
Percent hispanic	-0.140	0.401	$1.207^{*}$	$2.521^{**}$	2.211**	4.011***
	(0.125)	(0.378)	(0.697)	(1.006)	(1.061)	(0.888)
Percent Trump	$-0.514^{**}$	$-1.580^{**}$	$-2.350^{*}$	$-3.727^{*}$	-6.603***	$-6.291^{***}$
	(0.245)	(0.743)	(1.368)	(1.974)	(2.082)	(1.741)
Percent internet	0.123	-0.329	-0.265	0.547	$2.304^{*}$	0.493
	(0.136)	(0.413)	(0.761)	(1.098)	(1.158)	(0.968)
lag.Median age	-0.030	0.931	-0.038	0.090	-1.152	-0.450
	(0.220)	(0.668)	(1.230)	(1.775)	(1.871)	(1.565)
lag.Percent educ	-0.491	1.104	3.763	-2.310	7.830**	-1.478
	(0.440)	(1.336)	(2.462)	(3.552)	(3.746)	(3.134)
lag.Percent female	0.317	0.388	0.761	2.550	1.313	2.763
	(0.236)	(0.715)	(1.318)	(1.901)	(2.005)	(1.677)
lag.Percent black	-0.574	-1.103	0.324	-2.277	0.788	-1.499
	(0.590)	(1.789)	(3.296)	(4.756)	(5.016)	(4.195)
lag.Percent white	-0.682	$-5.108^{**}$	-4.417	-5.285	-0.024	-2.981
	(0.703)	(2.134)	(3.931)	(5.672)	(5.982)	(5.004)
lag.Percent hispanic	-0.032	-0.113	-0.869	-1.971	0.509	-0.603
	(0.176)	(0.534)	(0.984)	(1.420)	(1.498)	(1.253)
lag.Percent Trump	0.305	$3.929^{***}$	$4.546^{**}$	3.013	4.203	1.649
	(0.390)	(1.183)	(2.179)	(3.144)	(3.315)	(2.773)
lag.Percent internet	0.208	-0.116	-2.583	0.496	-5.738*	0.141
	(0.358)	(1.087)	(2.002)	(2.889)	(3.046)	(2.548)
Num.Obs.	67	67	67	67	67	67
R2	0.468	0.706	0.769	0.865	0.878	0.934
R2 Adj.	0.298	0.612	0.695	0.821	0.839	0.913
RMSE	0.41	1.24	2.29	3.31	3.49	2.92

 Table 9: Differential Effects across Time

Note: \* p < 0.1, \*\* p < 0.05, \*\*\* p < 0.01. All control variables are standardized for comparison. All regressions use the SLX model, our preferred specification.

rates compared to 4.8, 3.7, and -4.2 percentage points change in male vaccination rate.

*Race/Ethnicity*: unsurprisingly, there are more differences across the determinants of vaccination rates for the different race/ethnic groups. For the white vaccination rate the results are in line with those in Table 6 in terms of sign, magnitude and statistical significance. The main determinants of the black vaccination rate are the indirect effects, in particular, the spatially lagged median age (-3.832) and the spatially lagged percent Hispanic. Lastly, the main determinants of the Hispanic vaccination rate are education (4.882) and the percent access to internet (-3.256).

Age Groups: for the age groups the results are also much in line with those in Table 6 in terms of sign and statistical significance. We do note some changes in the magnitude of the estimated coefficients for the 45-64 age group and ages 65 and up, especially for black and white population, and Trump votes. Some of the main differences across groups are that education and Hispanic population are not determinants of age 65+ vaccination rate, while percent black and white are not statistically different from zero for the vaccination rate for ages 25-44. In terms of political preference, the results suggest that one standard deviation increase in the share of Trump votes is associated with an decrease of -8.7, -8.1, and -10.1 percentage points in the vaccination rates of ages 25-44, ages 45-64 and ages 65 and up.

*Timing*: when looking at the vaccination rate across months, we can investigate how these determinants changed over time. These results should be largely driven by the eligibility groups as described in Table 2. The only two variables that are statistically significant in all 6 models (Jan - Jun) are median age and the percent vote in Trump. While in January we see a negative relationship between age and vaccination rate (only health care workers and people in nursing homes eligible), it turns positive and increases in an inverted U shape, peaking in April. The magnitude of share of Trump votes is continuously increasing over time getting to over negative 6 percentage points by May. This growth pattern is largely observed in the other variables such as education, female population, and black, white and Hispanic population.

Lastly, we want to focus on two periods of time: February and May. February is interesting because the vaccine was not yet available for the general population, but there was a larger debate on the roll-out. The results show the direct and positive effect of age, education and white population, and a negative direct effect of female and Trump votes. In this model, the spatially lagged white population is negatively associated with vaccination intake and the spatially lagged votes in Trump are positively associated with vaccination rates. Then, we look in May, when most adults were already eligible to start the vaccination schedule. The direct effects are similar to those in February, but in May, access to internet and the spatially lagged education positively impacted vaccination rates, while the spatially lagged access to internet is negatively associated with vaccination rate.

#### 5. DISCUSSION AND CONCLUSION

This paper evaluates how demographic, economic and political factors help explain vaccination rates across counties in the state of Florida. Using a spatial econometric analysis we find that the political preference consistently associates with vaccination rate, while demo-

graphic and economic characteristic estimates seems to be less relevant in explaining overall vaccination rates or vaccination rates across sub-population groups.

We contribute to the existing and growing literature on Covid-19 vaccinations in two ways. Firstly, we explore the effect of political preference on vaccination rates in a local level – counties. Political preferences may capture two larger trends which we are unable to disentangle: (i) influence of political discourse and (ii) attitudes and health behavior. Secondly, we implement an spatial econometric analysis which take into account potential spillovers due to mobility and migration, as well as inter-county ties between individuals.

Politics and ideology can play a strong role in the decisions we make about our health. The different effects of political affiliation can be explained by the make up of and the rhetoric of political figures associated the party. The direct effects found between Covid-19 vaccinations and political preferences is consistent with the literature which finds a significant relationship between political preferences and vaccination uptake, especially along party lines. Additionally, recent studies report those who identify as Republicans, or lean more conservative, are less likely to get the vaccine than those with more liberal leanings (Young et al., 2022; Kaushal et al., 2022).

Regarding the other demographic results, some studies find that there is a non-linear relationship between age and Covid-19 vaccination rates, while others find that vaccine hesitancy is less common among older adults (Kadoya et al., 2021; Schwarzinger et al., 2021; Beleche et al., 2021; Malik et al., 2020). Additionally, both the infection rate for the virus and its effects have been found to be worse for older adults than for younger groups. Similarly, the correlation between gender and vaccination rate was consistent with the literature where more females among the population is associated with a lower vaccination rate (Malik et al., 2020; Nikolovski et al., 2021; Kadoya et al., 2021; Beleche et al., 2021; Schwarzinger et al., 2021).

Although no statistically significant relationship was present between size of Hispanic population and vaccination rates in January and February, we saw some positive and statistically significant effects from March to June. A potential explanation is the result of informational campaigns launched by a variety of organizations which targeted minority populations during the early months of vaccine availability. By providing more information on the vaccine, these campaigns could have persuaded those in the Hispanic population to get vaccinated.

As the Covid-19 pandemic ends, but the virus becomes more seasonal, as well as new health threats become prevalent it is important to understand the factors that are mostly associated immunization intake. This should aid in the development of policies and information campaigns to target certain population groups to minimize the social, health, and economic impacts.

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# APPENDIX

## A. BORDERING STATES

One concern with the spatial analysis focusing on Florida alone is that by the nature of the analysis we omit bordering counties of first and higher orders. In this section we include first only the bordering counties to Florida in Georgia and Alabama (Table A1), and then we expand to include all counties in these states (Table A2). The direct results are consistent with those in the main analysis, but there are some changes in the indirect results. For instance, when we include bordering counties to Florida only, in the SLX model the spatially lagged percent Trump vote becomes statistically significant (negative). When including all counties in Georgia and Alabama, in all spatial models the percent vote to Trump becomes statistically significant (positive). While the results are mixed depending on counties included, this is not unexpected given the change in the sample. However, these does corroborate the previous analysis and reinforce the political preference findings.

OLSSLXSDMSDEMMedian age $3.445^{***}$ $4.329^{***}$ $4.417^{***}$ $4.511^{***}$ $(0.602)$ $(0.686)$ $(0.589)$ $(0.607)$ Percent white $8.433^{**}$ $10.628^{**}$ $10.127^{***}$ $10.997^{***}$ $(3.883)$ $(4.145)$ $(3.577)$ $(3.724)$ Percent black $0.933$ $2.588$ $1.867$ $2.213$ $(3.794)$ $(4.059)$ $(3.495)$ $(3.708)$ Percent hispanic $0.581$ $1.561^{**}$ $1.542^{**}$ $1.678^{**}$ $(0.632)$ $(0.747)$ $(0.642)$ $(0.721)$ Percent educ $4.045^{***}$ $3.841^{**}$ $3.738^{***}$ $3.730^{***}$ $(1.375)$ $(1.518)$ $(1.304)$ $(1.353)$ Percent internet $-0.429$ $-0.617$ $-0.537$ $-0.762$ $(1.201)$ $(1.237)$ $(1.065)$ $(1.074)$ Percent female $-2.694^{***}$ $-2.572^{***}$ $-2.619^{***}$ $(0.665)$ $(0.747)$ $(0.642)$ $(0.672)$ Percent Trump $-9.861^{***}$ $-11.50^{***}$ $-12.213^{***}$ $(1.624)$ $(2.239)$ $(1.937)$ $(2.055)$ lag.Median age $0.927$ $2.381$ $0.741$ $(1.500)$ $(1.458)$ $(1.213)$ $(1.234)$ lag.Percent white $-14.926$ $-7.102$ $-6.470$ $(7.780)$ $(6.685)$ $(6.453)$ $(6.453)$ lag.Percent hispanic $0.270$ $0.694$ $0.066$ $(1.090)$ $(0.961)$ $(0.965$		G	eorgia.		
Median age $3.445^{***}$ $4.329^{***}$ $4.417^{***}$ $4.511^{***}$ $(0.602)$ $(0.686)$ $(0.589)$ $(0.607)$ Percent white $8.433^{**}$ $10.628^{**}$ $10.127^{***}$ $10.997^{***}$ $(3.883)$ $(4.145)$ $(3.577)$ $(3.724)$ Percent black $0.933$ $2.588$ $1.867$ $2.213$ $(3.794)$ $(4.059)$ $(3.495)$ $(3.708)$ Percent hispanic $0.581$ $1.561^{**}$ $1.542^{**}$ $1.678^{**}$ $(0.632)$ $(0.747)$ $(0.642)$ $(0.721)$ Percent educ $4.045^{***}$ $3.841^{**}$ $3.730^{***}$ $(1.375)$ $(1.518)$ $(1.304)$ $(1.353)$ Percent internet $-0.429$ $-0.617$ $-0.537$ $-0.762$ $(1.201)$ $(1.237)$ $(1.065)$ $(1.074)$ Percent female $-2.694^{***}$ $-2.619^{***}$ $-2.619^{***}$ $(0.665)$ $(0.747)$ $(0.642)$ $(0.672)$ Percent Trump $-9.861^{***}$ $-11.67^{***}$ $-11.219^{***}$ $(1.624)$ $(2.239)$ $(1.937)$ $(2.055)$ lag.Median age $0.927$ $2.381$ $0.741$ $(1.624)$ $(2.239)$ $(1.937)$ $(2.057)$ lag.Percent white $-14.926$ $-12.345$ $-13.904^{*}$ $(9.294)$ $(8.060)$ $(7.571)$ $(7.780)$ $(6.685)$ $(6.453)$ lag.Percent hispanic $0.270$ $0.694$ $0.066$ $(1.709)$ $(1.213)$ $(3.730)$ $(3.478)$ $(3.94)$ <		OLS	SLX	SDM	SDEM
$0.602$ $(0.602)$ $(0.686)$ $(0.589)$ $(0.607)$ Percent white $8.433^{**}$ $10.628^{**}$ $10.127^{***}$ $10.997^{***}$ $(3.883)$ $(4.145)$ $(3.577)$ $(3.724)$ Percent black $0.933$ $2.588$ $1.867$ $2.213$ $(3.794)$ $(4.059)$ $(3.495)$ $(3.708)$ Percent hispanic $0.581$ $1.561^{**}$ $1.542^{**}$ $1.678^{**}$ $(0.632)$ $(0.747)$ $(0.642)$ $(0.721)$ Percent educ $4.045^{***}$ $3.841^{**}$ $3.778^{***}$ $3.730^{***}$ $(1.375)$ $(1.518)$ $(1.304)$ $(1.353)$ Percent internet $-0.429$ $-0.617$ $-0.537$ $-0.762$ $(1.201)$ $(1.237)$ $(1.065)$ $(1.074)$ Percent female $-2.694^{***}$ $-2.572^{***}$ $-2.619^{***}$ $(0.665)$ $(0.747)$ $(0.642)$ $(0.672)$ Percent Trump $-9.861^{***}$ $-11.607^{***}$ $-11.505^{***}$ $(1.624)$ $(2.239)$ $(1.937)$ $(2.055)$ lag.Median age $0.927$ $2.381$ $0.741$ $(1.624)$ $(2.239)$ $(1.937)$ $(2.647)$ lag.Percent white $-14.926$ $-12.345$ $-13.904^{*}$ $(9.294)$ $(8.060)$ $(7.571)$ lag.Percent hispanic $0.270$ $0.694$ $0.066$ $(1.090)$ $(0.961)$ $(0.965)$ lag.Percent internet $4.879$ $4.694$ $4.359$ $(3.655)$ $(3.140)$ $(2.878)$	Median age	$3.445^{***}$	4.329***	4.417***	4.511***
Percent white $\hat{8}.433^{**}$ $10.628^{**}$ $10.127^{***}$ $10.997^{***}$ Percent black $0.933$ $2.588$ $1.867$ $2.213$ $(3.794)$ $(4.059)$ $(3.495)$ $(3.724)$ Percent hispanic $0.581$ $1.561^{**}$ $1.542^{**}$ $1.678^{**}$ $(0.632)$ $(0.747)$ $(0.642)$ $(0.721)$ Percent duc $4.045^{***}$ $3.841^{**}$ $3.778^{***}$ $3.730^{***}$ $(1.375)$ $(1.518)$ $(1.304)$ $(1.353)$ Percent internet $-0.429$ $-0.617$ $-0.537$ $-0.762$ $(1.201)$ $(1.237)$ $(1.065)$ $(1.074)$ Percent female $-2.694^{***}$ $-2.572^{***}$ $-2.697^{***}$ $(0.665)$ $(0.747)$ $(0.642)$ $(0.672)$ Percent Trump $-9.861^{***}$ $-11.505^{***}$ $-12.219^{***}$ $(1.624)$ $(2.239)$ $(1.937)$ $(2.055)$ lag.Median age $0.927$ $2.381$ $0.741$ $(1.624)$	0	(0.602)	(0.686)	(0.589)	(0.607)
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	Percent white	8.433**	$10.628^{**}$	10.127***	10.997***
Percent black $0.933$ $2.588$ $1.867$ $2.213$ (3.794) $(4.059)$ $(3.495)$ $(3.708)$ Percent hispanic $0.581$ $1.561^{**}$ $1.542^{**}$ $1.678^{**}$ $(0.632)$ $(0.747)$ $(0.642)$ $(0.721)$ Percent educ $4.045^{***}$ $3.841^{**}$ $3.738^{***}$ $3.730^{***}$ $(1.375)$ $(1.518)$ $(1.304)$ $(1.353)$ Percent internet $-0.429$ $-0.617$ $-0.537$ $-0.762$ $(1.201)$ $(1.237)$ $(1.065)$ $(1.074)$ Percent female $-2.694^{***}$ $-2.572^{***}$ $-2.619^{***}$ $-12.219^{***}$ $(0.665)$ $(0.747)$ $(0.642)$ $(0.672)$ Percent Trump $-9.861^{***}$ $-11.505^{***}$ $-12.219^{***}$ $(1.624)$ $(2.239)$ $(1.937)$ $(2.055)$ lag.Median age $0.927$ $2.381$ $0.741$ $(1.500)$ $(1.458)$ $(1.213)$ lag.Percent white $-14.926$ $-12.345$ $-13.904^*$ $(3.709)$ $(3.290)$		(3.883)	(4.145)	(3.577)	(3.724)
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	Percent black	0.933	2.588	1.867	2.213
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$		(3.794)	(4.059)	(3.495)	(3.708)
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	Percent hispanic	0.581	1.561**	1.542**	$1.678^{**}$
$\begin{array}{cccccccccccccccccccccccccccccccccccc$		(0.632)	(0.747)	(0.642)	(0.721)
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	Percent educ	4.045***	3.841**	$3.778^{***}$	3.730***
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$		(1.375)	(1.518)	(1.304)	(1.353)
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	Percent internet	-0.429	-0.617	-0.537	-0.762
$\begin{array}{cccccccccccccccccccccccccccccccccccc$		(1.201)	(1.237)	(1.065)	(1.074)
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	Percent female	$-2.694^{***}$	$-2.572^{***}$	$-2.619^{***}$	$-2.697^{***}$
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$		(0.665)	(0.747)	(0.642)	(0.672)
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	Percent Trump	$-9.861^{***}$	$-11.667^{***}$	$-11.505^{***}$	$-12.219^{***}$
$\begin{array}{cccccccccccccccccccccccccccccccccccc$		(1.624)	(2.239)	(1.937)	(2.055)
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	lag.Median age		0.927	2.381	0.741
$\begin{array}{cccccccccccccccccccccccccccccccccccc$			(1.500)	(1.458)	(1.213)
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	lag.Percent white		-14.926	-12.345	-13.904*
$\begin{array}{cccccccccccccccccccccccccccccccccccc$			(9.294)	(8.060)	(7.571)
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	lag.Percent black		-8.180	-7.102	-6.470
$\begin{array}{cccccccccccccccccccccccccccccccccccc$			(7.780)	(6.685)	(6.453)
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	lag.Percent hispanic		0.270	0.694	0.066
$\begin{array}{cccccccccccccccccccccccccccccccccccc$			(1.090)	(0.961)	(0.965)
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	lag.Percent educ		-1.724	0.723	-0.516
$\begin{array}{cccccccccccccccccccccccccccccccccccc$			(3.709)	(3.290)	(2.840)
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	lag.Percent internet		4.879	4.694	4.359
lag.Percent female $0.113$ $-0.994$ $-0.040$ $(1.715)$ $(1.549)$ $(1.421)$ lag.Percent Trump $8.534^{**}$ $6.054^{*}$ $8.965^{***}$ $(3.730)$ $(3.478)$ $(3.081)$ rho $-0.370^{**}$ $(0.172)$ lambda $-0.414^{**}$ $(0.176)$ Num.Obs. $83$ $83$ R2 $0.849$ $0.875$ R2 Adj. $0.833$ $0.845$ BMSE $4.49$ $4.09$ $3.94$ 3.92			(3.655)	(3.140)	(2.878)
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	lag.Percent female		0.113	-0.994	-0.040
lag.Percent Trump $8.534^{**}$ $6.054^*$ $8.965^{***}$ (3.730)(3.478)(3.081)rho $-0.370^{**}$ (0.172)lambda $-0.414^{**}$ (0.176)Num.Obs.8383R20.8490.875R2 Adj.0.8330.845BMSE4 494 093 943 92			(1.715)	(1.549)	(1.421)
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$	lag.Percent Trump		8.534**	6.054*	8.965***
rho $-0.370^{**}$ (0.172)         lambda $-0.414^{**}$ (0.176)         Num.Obs.       83       83         R2       0.849       0.875         R2 Adj.       0.833       0.845         BMSE       4 49       4 09       3 94       3 92			(3.730)	(3.478)	(3.081)
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	rho			-0.370**	
lambda $-0.414^{**}$ (0.176)         Num.Obs.       83         R2       0.849         0.833       0.845         BMSE       4.49       4.09       3.94       3.92				(0.172)	
Num.Obs.     83     83       R2     0.849     0.875       R2 Adj.     0.833     0.845       BMSE     4.49     4.09     3.94     3.92	lambda				-0.414**
Num.Obs.     83     83       R2     0.849     0.875       R2 Adj.     0.833     0.845       BMSE     4.49     4.09     3.94     3.92					(0.176)
R2       0.849       0.875         R2 Adj.       0.833       0.845         BMSE       4.49       4.09       3.94       3.92	Num.Obs.	83	83		
R2 Adj. 0.833 0.845 RMSE 4 49 4 09 3 94 3 92	R2	0.849	0.875		
BMSE 449 409 394 392	R2 Adj.	0.833	0.845		
	RMSE	4.49	4.09	3.94	3.92

 Table A1: Robustness check using border counties from Alabama and Georgia.

Note: \* p < 0.1, \*\* p < 0.05, \*\*\* p < 0.01. All control variables are standardized for comparison.

	OLS	SLX	SDM	SDEM
Median age	2.662***	1.854**	1.772***	2.015***
-	(0.644)	(0.765)	(0.612)	(0.610)
Percent white	12.216***	9.403**	7.764**	7.998**
	(3.665)	(3.990)	(3.190)	(3.346)
Percent black	3.525	2.167	1.712	1.808
	(3.873)	(4.188)	(3.348)	(3.516)
Percent hispanic	$1.551^{*}$	0.733	0.716	0.961
	(0.846)	(1.009)	(0.806)	(0.831)
Percent educ	4.875***	4.154***	4.377***	4.398***
	(1.201)	(1.345)	(1.075)	(1.080)
Percent internet	-2.322**	-0.632	-0.480	-0.741
	(1.065)	(1.281)	(1.024)	(0.995)
Percent female	$-3.169^{***}$	$-2.641^{***}$	-2.400***	-2.530***
	(0.592)	(0.637)	(0.510)	(0.523)
Percent Trump	$-10.260^{***}$	$-8.659^{***}$	$-7.513^{***}$	-7.776***
	(1.733)	(2.335)	(1.867)	(1.794)
lag.Median age		0.574	-0.560	1.630
		(1.413)	(1.143)	(1.462)
lag.Percent white		9.332	-1.747	2.180
		(7.730)	(6.220)	(8.155)
lag.Percent black		1.602	-1.894	-1.662
		(7.698)	(6.155)	(8.261)
lag.Percent hispanic		-1.002	-0.957	0.656
		(1.500)	(1.201)	(1.655)
lag.Percent educ		2.409	-2.232	-0.952
		(2.703)	(2.183)	(2.824)
lag.Percent internet		-6.213**	-2.324	-2.112
		(2.437)	(1.960)	(2.471)
lag.Percent female		-2.813**	0.115	-1.328
		(1.229)	(1.011)	(1.363)
lag.Percent Trump		-7.560*	0.641	-4.392
		(4.006)	(3.275)	(4.128)
rho			$0.611^{***}$	
			(0.059)	
lambda				$0.629^{***}$
				(0.058)
Num.Obs.	293	293		
R2	0.478	0.509		
R2 Adj.	0.463	0.480		
RMSE	9.11	8.83	7.27	7.27

 Table A2:
 Robustness check using all counties from Alabama and Georgia.

Note: \* p < 0.1, \*\* p < 0.05, \*\*\* p < 0.01. All control variables are standardized for comparison.