Heterogenous effects on mobility and consumption in response to easing stay at home orders during the COVID-19 pandemic

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Abstract

This paper explores human mobility responses to city-level reopenings for a sample of US cities during the COVID-19 pandemic. With the use of cellphone tracking and business financial data, I employ a variety of reduced form econometric techniques to estimate how the general US population responded to city level stay at home order removals. I observe modest responses in visiting patterns to essential industries following the removal of stay at home orders, and with larger impacts at industries deemed to be either semi-essential or non-essential. Industry specific models suggest mobility patterns shifting towards industries more prone to spread the COVID-19 virus. Further, I find there to be a strong increase in small business revenue following the removal of stay at home orders.

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1 Introduction

One of the largest tactics used to combat the spread of the COVID-19 virus has been increasing social distancing. Reducing the number of face to face interactions has been shown to greatly reduce the likelihood of spreading the virus (Courtemanche et al., 2020). Government officials have mandated policies to increase the proportion of the population who are socially distancing. These policies, known as non-pharmicitucial interventions, include closing schools, gyms, non-essential businesses, banning large gatherings, and in most interest to this paper, issuing stay at home orders. While not all US states issued a stay at home order, as of April 2020 96% of US residents were living under some form of a stay at home order (Alexander and Karger, 2020). While the body of literature surrounding the COVID-19 pandemic strongly supports socially distancing as a detergent for spreading the virus, increased levels of social distancing comes with a great cost. The US Bureau of Labour Statistics reported the unemployment rate peaking at 14.7% in April, the same month the majority of the US was under a stay at home order. Further, Kahn et al. (2020) found job vacancies to be 30% lower than their pre-pandemic levels due to COVID-19. As a result, there has been a strong push to begin reopening the economy and promoting economic activity.

This study focuses on exploring the changes in mobility and consumption patterns in response to US cities lifting their stay at home (SAH) orders. I use cell phone location data to map the aggregate mobility decisions of US residents leading up to and following the removal of stay at home orders at the county level. I find that removing SAH orders causes immediate increases in mobility patterns to semi-essential industries, and more modest increases in mobility patterns to non-essential industries. With the increase in mobility, I also document a roughly 10% increase in small business revenue as a result of removing stay at home orders. The impacts from removing stay at home orders are also heterogenous across socioeconomic groups, with small businesses in republican leaning counties seeing twice as large an increase in their daily revenues compared to similar businesses in democratic counties. Findings across income groups are less concise, while the number of businesses reopened quicker in lower income counties, the differences in changes to mobility patterns across income quantiles is insignificant.

One of the earliest papers to study the impact of social distancing on the spread of COVID-19 was done by Fang et al. (2020) who found that social distancing in Wuhan prevented COVID-19 cases from rising 64% in cities within the neighbouring Hubei province.

Similar work is done using US data, finding that 3-4 months of heavy social distancing would prevent 1.7 million COVID-19 related deaths (Greenstone and Nigam, 2020). Alexander and Karger (2020) find the immediate effect of issuing SAH orders led to a mobility decline of 8% the day after the policies were implemented. The earliest paper to study the impact of SAH orders on COVID-19 outcomes in the US was done by Friedson et al. (2020) who used a synthetic control research design to approximate a reduction of 172 cases per 100k just one month after the stay at home order in California was implemented.

Reductions in mobility patterns in response to implementing SAH orders has been found to vary across socioeconomic groups. Jay et al. (2020) find that residents of low income areas are not able to socially distance as much as residents in higher income areas, and as a result were put at a greater risk of contracting the COVID-19 virus. Further, behaviour in response to social distancing varies across political lean where residents of republican counties are more likely to avoid socially distancing and are less likely to change their mobility patters compared to residents of democratic counties (Painter and Qiu, 2020; Allcott et al., 2020; van Holm et al., 2020).

There is a gap in the body of literature surrounding mobility responses in terms of removing stay at home orders. One paper which discusses the removal of stay at home orders, done by Nguyen et al. (2020), uses state level reopening information along with spatial regression discontinuity and event study frameworks to find that the largest increases in mobility patterns came from states who were late to implement the stay at home policies. The authors report point estimates between a 6-8% increases in mobility patterns after states removed SAH orders.

My research extends on the work by Nguyen et al. (2020) by estimating the policy changes at a city rather than state level, and by estimating impacts across socioeconomic groups. While it is true that some stay at home orders are lifted at the state level, many counties and cities are given the discretion to remove or implement stay at home policies based on their estimated COVID-19 risk. For this reason, it has been found that estimates using state-level SAH policies were found to be "economically small, statistically insignificant and of the wrong sign" (Goolsbee and Syverson, 2020).

This paper contributes to the rapidly evolving body of literature surrounding mobility patterns and consumption decisions during the COVID-19 pandemic in three ways. First, it is the first paper to estimate the impact of removing SAH orders at the county level. Second, it applies a variety of econometric techniques beyond a standard event study framework to reach industry mobility estimates. Lastly, this paper addresses and aims to overcome biases that arise from heterogenous treatment dates in difference-in-differences estimators.

2 Data

There has been a surge in highly detailed mobility data available for researchers as a result of the push against the COVID-19 pandemic. One common method of tracking human mobility patterns is to follow the locations of cell phones. There are a variety of companies who collect this data, and their data has become ever so popular with regards to understanding the mobility decisions of the public. One of the earliest uses of the cell phone mobility patterns came using data from SafeGraph to estimate a consumer choice model studying workers' preferences for lunches in California (Athey et al., 2018). Similarly, the same data from SafeGraph used to find that families with opposing political views spent up to 50 minutes less together during thanksgiving dinner compared to families with similar political beliefs (Chen and Rohla, 2018). In both cases, the use of cell phone data allowed the researcher to know about the mobility choices of their target population.

For this study, I use the SafeGraph foot traffic patterns dataset alongside their CORE points of interest dataset to construct daily totals for the number of visitors to a point of interest within a given industry on a given day. I use mobility data from January 1 - June 30 in 2020 and 2019. I chose to focus on a subset of locations and industries which I determined to be of interest. The decision to work off a subset of locations was made to ensure I was collecting accurate policy implementation dates at the most granular level. This is imperative to avoid any spurious or biased results as many of the hardest hit counties implemented non-pharmaceutical interventions prior to their state (Goolsbee and Syverson, 2020).

I construct a balanced panel of the daily total visits to all points of interest falling within a given industry and county on a daily basis for the period January 1, 2020 - June 30, 2020. Summary statistics from this panel can are presented in Table 2. We can see the visit data is largely right skewed where the median industry receives 220 visits per day, yet the mean industry receives 8,289 visits per day. Fast food restaurants receive the most daily traffic while train stations receive the least.

While knowing the mobility patterns provides useful information on behaviour during the pandemic, it arguably does not paint a complete picture with regards to the impact of reopening the economy. The largest argument for removing stay at home orders is to help rebound the economy due to the lack of consumption during the pandemic. I supplement the mobility data with financial spending data for small businesses throughout the US. Small businesses took the hardest hit during the lockdown as small business revenue was estimated to have fallen 35% year-over-year as of April 17th. In comparison, spending at larger firms over the same period increased by 8%, and online firms saw spending increase 71% (Alexander and Karger, 2020). Therefore, this paper will also study whether there was an attributable increase to small business revenue due to the removal of stay at home orders.

I use financial transaction data collected by the fintech company Womply to estimate the daily transactions recorded on their platform for a panel of more than 1 million US small businesses[1]. Due to the anonymity of this dataset, it has been made publicly available by Chetty et al. (2020a) after being aggregated to the city level. The data series is presented as the seven day moving average year over year change in total revenues for small businesses indexed against their pre-pandemic revenues[2].

To observe heterogenous impacts across socioeconomic groups, I construct county-level measures of income and political lean. Income quantiles are constructed using aggregate household income measures from the US Census. A county is determined to be a high income county if it falls above the national median aggregate income quantile, and similarly is determined to be a low income county if it falls below the national median quantile. Political lean indicators for each county are constructed using the 2016 federal election vote counts collected from the MIT Election Data and Science Lab database. If the majority of votes within a county were for Donald Trump the county was tagged republican, otherwise the county was tagged democratic.

I collect COVID-19 testing, cases and mortality rates per 100K at the city level from the New York Times COVID database[3]. City level summary statistics for each city can be found in Table 3. Non-pharmaceutical intervention data was collected primarily by hand through web searches and news releases for each city. Table 1 shows the earliest, median and latest date at which stay at home orders, restrictions on nonessential businesses, restaurants, gyms and movie theaters were lifted. Out of my sample of 51 cities, all cities had removed their restriction on nonessential businesses and only 57% had removed their

[1] Small businesses determined as receiving no more than $250K in revenue during January 2020.

[2] Refer to Chetty et al. (2020a) for further information on the dataset.

[3] Data and further information made publicly available per their github: https://github.com/nytimes/covid-19-data

stay at home order. On average, stay at home orders and restrictions on gyms were the last NPIs to be lifted. A timeline of the COVID cases, deaths and stay at home order duration can be seen for each city in Figure 1. We can see that there is a large amount of variance around when stay at home orders were lifted, including some cities which never implemented a stay at home order, and some which had a stay at home order in place through the end of June and into July. Of the total 51 cities in my sample, 11 cities never implemented a SAH order, 11 have yet to remove their SAH order[4], and 29 have implemented and removed their SAH order.

3 Empirical strategy

One of the largest motivations for this section comes from the theoretical work on difference-in-differences estimates with different treatment dates and treatment effects (Goodman-Bacon, 2018). As the dates in which each city implemented and removed their SAH orders, it is plausible to believe the impacts of these policy decisions vary. Alexander and Karger (2020) find states which issued stay at home orders at later dates had a lower proportion of the population decrease their mobility out of their homes. If this is true for reopening the economy, we could expect that later cities to remove the stay at home orders will see lesser impacts in terms of increased mobility. The main result from Goodman-Bacon (2018) is that a two-way fixed effect difference-in-differences model with heterogenous treatment dates is simply a weighted average of all the possible two-way difference-in-differences estimators.

In order to address and better understand which control groups I am using in my model, I run three varying difference-in-differences specifications. The first being the naive two-way fixed effect difference-in-differences model as described by Goodman-Bacon (2018), where I include an indicator for whether a given county has removed their SAH order with county and time fixed effects.[5] This model uses each city that did not turn off its stay at home order at the given date of the treated city as a control group. With all the combinations of cities being used as both treated and control groups, it becomes difficult to best understand which city is a control for which treatment. I improve the quality of

[4]As of June 30, 2020

[5]The two-way fixed effect model has been found to be the common approach in dealing with heterogenous treatment dates. Half of the 93 difference-in-differences papers published to top journals in 2014/15 employing this approach to overcome heterogenous treatment dates (Goodman-Bacon, 2018)

my control groups using a nearest neighbor propensity score matching algorithm. I use the 2019 visit patterns for each city, both treated and untreated, to find the treated city's most similar control city. It is also worth noting that since I have some cities which never issued a SAH order, and some which have yet to remove their SAH order that is in place, I will have two sets of control groups for each treated city. Lastly, I follow the methodology laid out in Abadie et al. (2010) and use the donor pool of all the control cities to generate a synthetic control city for each treated city. I outline the specifics of each of these methods in the following subsections.

3.1 Two-way fixed effect model

As mentioned above, the two-way fixed effect model includes an indicator variable for whether a given city lifted their SAH order with city and time fixed effects. The specific empirical speciation is the following,

$$\log(Visits_{ct})|_{i\in I} = \tau DID + \gamma_c + \gamma_t + \phi X_{ct} + \epsilon_{ct} \tag{1}$$

As observed in Table 2, foot traffic counts are highly right skewed, therefore I use log visits as my dependent variable. The coefficient of interest τ represents the percentage change in visits within industry group $i \in I$. γ_c and γ_t are county and time fixed effects and X_{ct} are covariates that are variant over time and across counties including COVID cases, tests and deaths, the removal of other NPI orders, and weekend indicators. Robust standard errors are clustered at the state level as we would counties within the same state to exhibit similar mobility behaviours.

3.2 Nearest neighbour matching

In order to find the nearest neighbour match for each of my treated cities, I compute the propensity score for each city with the following probit specification.

$$Y_c = f(Visits_{ct}) + X_c + \epsilon_{ct} \tag{2}$$

Where Y_c is an indicator for whether city c removes their SAH order, $f(visits_{ct})$ is a fourth-degree polynomial capturing the visit trend for cities during January 1, 2019 through May 2019. Since the objective is to create a control group to represent the behaviour of the treated city had they not removed their SAH order, using visits prior to the COVID-19 pandemic would identify the most similar behaving cities. There still may be other factors however that can cause cities to behave differently during the pandemic, which is why I also include a matrix of controls specific to each city, X_c, this contains data on the COVID cases, death rate and testing rate, the 2019 city population, the number of merchants open and their revenues as of March 2020.

Since there are two potential pools of control groups, cities which never implemented SAH orders, and cities which never removed their SAH order, I preform two sets of matches. These pairs can be seen in Figures 6 and 7 where I plot standardized visit trends for 2019.

With the matched data, I assign the corresponding treatment date to each control city and run the following model for each industry i.

$$\log(Visits_{ct})|_{i \in I} = \tau DID_{ct} + \beta_1 TREAT_c + \beta_2 POST_t + X_{ct} + \epsilon_{ct} \tag{3}$$

Where $POST$ is an indicator for whether the total visits are recorded after the city pair's treatment date, $TREAT$ is an indicator for whether the city removes its SAH order, DID is the interaction of both the $TREAT$ and $POST$ variables, and X_{ct} is the same matrix of control variables. Robust standard errors are again clustered at the state level.

3.3 Synthetic control group

One downside from using nearest-neighbour matching comes from using only one city as a control group. Following a similar methodology as Friedson et al. (2020), who constructed a synthetic control group to measure the impact of California's SAH order on their COVID case rate, I construct synthetic control groups for each of my treated cities. Friedson et al. (2020) uses observable characteristics of other states pertaining to the rate at which the COVID-19 virus would spread, i.e. population density, urbanicity, emergency decrees in the area, travel restrictions, and COVID testing information. Since I am interested in mobility patterns to various industries, I use the following observable characteristics: Womply merchant revenue and proportion of open businesses, COVID case and death rates per 100K, low income earnings and employment, city 2019 population rates, credit card spending and UI claims.[6]

With this dataset, I construct synthetic control groups for each industry of each treated

[6]Many of the covariates used here were aggregated and provided by Chetty et al. (2020b). Please refer to their open github page for further details: https://github.com/OpportunityInsights/EconomicTracker

city based on the above observable characteristics. Then within each industry group, I take the average distance in terms of total visits between the treated and synthetic control group two weeks after implementing the SAH order and average over these gaps fo construct my synthetic control estimate by each industry.[7] With this approach, it is difficult to estimate accurate standard errors and therefore standard errors for synthetic control group estimates were omitted. For proper synthetic control difference-in-differences estimation and inference please refer to Arkhangelsky et al. (2019).[8]

3.4 Event Study Estimation

In addition to the above difference-in-differences models, I use an event study framework to estimate mobility patterns leading up to and following the removal of SAH policies. In this specific setting, this is particularly useful as there are daily changes in information available to the public and potentially other drivers of mobility patterns beyond the SAH orders. If this were the case, an event study would show there being a violation of the parallel trends assumption prior to treatments. In addition, event study models allow for easy visual comparison of mobility patterns across industry, income and political lean slices.

My general event study specification is the following,

$$y_{ct} = \sum_{s=-10}^{10} \beta_s 1(\text{Removed SAH})_{c,t-s} + \gamma_c + \gamma_t + \phi X_{ct} + \epsilon_{ct} \tag{4}$$

Where y is either the total visits to a specific industry group, the daily revenue index to small businesses, or the number of small businesses open at time t in county c. The event study coefficients $\{\beta\}_{-10}^{10}$ measure the impact of removing the SAH order s days relative to when it was issued. These coefficients are normalized against the day before the SAH order was relaxed. X is again a matrix of controls including COVID cases, tests, deaths, and indicators for other non-pharmaceutical interventions. Robust standard errors are clustered at the state level.

In the event study regressions, I estimate mobility patterns for a subset of industries at a time. Essential businesses are comprised of the following: Automobile repair, banks and

[7] While this is a daunting task to iterate through each industry / city iteration, the R Synth package does most of the heavy lifting (Abadie et al., 2011).

[8] At the time of writing this paper, their R package for estimation was in its alpha stage and was unstable for use.

financial services, grocery stores, and train stations. Non-essential services are comprised of the follwowing industries: Bars and nightclubs, Cafes, Juice bars and dessert, Full service and limited service restaurants, gyms, and movie theaters. Semi-essential services are comprised of the following industries: Hotels, Parks and playgrounds, and sporting goods stores.

I selected a window of ± 10 days around the removal of SAH orders to gather any weekday specific trends one week before and after SAH orders are removed. Longer intervals are likely to pick up other changing information and may be falsely attributed to the impact of removing SAH orders.[9]

4 Results

Difference-in-differences estimates for each industry can be seen in Figure 2, the coefficients along with standard errors can be found in Table 4. The results show that removing stay at home orders had a mild effect across all industries. Further the estimates are relatively consistent across the different specifications. Most notably there is a drastic yet insignificant decrease in the number of visits to grocery stores and an increase in the number of visits to limited service restaurants. This is indicative of consumers substituting their mobility and consumption decisions away from essential industries towards more semi and non-essential industries that come with increased risks of COVID-19 transmission.

Across all the model specifications, it is worth noting that the two-way fixed effect estimates (labelled unmatched FE) often tend to be the least significant estimates. This is likely due to the fact that, as stated in Goodman-Bacon (2018), the coefficients are representing a weighted average of all the treatment and control difference-in-differences pairs.

An additional observation when comparing across estimates, coefficients using cities which never implemented a stay at home order tend to have lower impacts relative to estimates where the control group was put into place showing the choice of the control group used has an impact on empirical results.

Event study coefficients are plotted in Figures 3 - 5. The first figure shows event study coefficients across essential, semi-essential and non-essential industries with a 90% confi-

[9] A 10 day window is also used by Alexander and Karger (2020), five day intervals by Nguyen et al. (2020), and both 10 and 5 day bins by Gupta et al. (2020).

dence interval[10]. We observe an insignificant impact of the stay at home order amongst essential industries, a significant[11] increase in the number of visits for semi-essential industries and a mildly significant increase in visits to non-essential industries. We see roughly a 10% increase in visits to semi-essential industries immediately following the implementation of stay at home orders, and a roughly a 6% increase in non-essential industries. This observation supports the claim found in Ahmed et al. (2020), that while twitter users were in favour of reopening the economy, many shared fears of a second wave. Non-essential industries in this setting are comprised of areas that are more susceptible to spreading COVID-19. If there is still a fear associated with contracting the virus from visits, we would expect to see less of an increase in non-essential industries.

Figure 4 breaks down the event study model into republican and democrat slices. It appears that republican counties weakly increased their visits in response to removing stay at home orders relative to democrats. While there does not appear to be much change in the semi-essential industries, we see larger increases in the non-essential and essential industries by republican counties. These results agree with further literature which finds republicans less likely to social distance and avoid riskier locations to spread COVID-19 (Chen and Qiu, 2020; Painter and Qiu, 2020).

There does not appear to be an significant difference across income levels in terms of response to removing stay at home orders, shown in Figure 8 of the appendix. This finding is surprising as others have found higher income areas to be able to social distance while low income areas are forced to remain working riskier jobs in public Jay et al. (2020).

Repeating the political and income slices with small business revenue, we see that there was a significant increase of about 8% five days following the removal of stay at home orders for small business revenue. Shown in Figure 5, this increase in revenue is slightly higher in republican counties which saw nearly twice as great a percentage increase in small business revenues relative to democratic counties a week after the stay at home order was removed.

One potential explanation as to the mild increases across industries could be simply that the businesses US residents wish to go to are simply not open yet. In a survey conducted by Balla-Elliott et al. (2020), the authors found that the median business did not plan to reopen until two weeks after stay at home orders were lifted. These results are supported by the event study in Figure 9 of the appendix which shows a gradual increase in the number

[10] The decision to show 90% CIs rather than 95% was made due to the amount of noise in the standard errors

[11] At $\alpha = 0.1$

of small businesses open leading up to and following the implementation of stay at home orders, meaning there is little evidence the number of firm reopenings were in response to removing SAH orders. The second panel shows republican businesses opened quicker than those in democratic counties which can suggest greater revenues observed above. Further, small businesses in lower income areas also reopened at a greater rate than high income areas. Dingel and Neiman (2020) find that workers living in high income areas are more able to work from home, where Coven and Gupta (2020) find that lower income workers in New York were less able to flee the city and more likely to continue working.

5 Conclusion

The COVID-19 pandemic led to the extreme slowdown of economic activity within the US. Facing much pressure and incentives to reopen, many cities have began relaxing their SAH orders. This paper finds that reopening the economy by easing SAH orders led to modest changes in mobility patterns for most industries with consumers substituting from points of interest in essential industries to places in semi and non-essential industries. Further, removing SAH orders led to an increase in small business revenues.

It is important to understand how the public will react to reopening policies as there is the ongoing risk of having cities repopen too quickly and spark a second wave of COVID-19. At the time this paper was written, the US recently saw total COVID-19 cases jump from 3 million to 4 million in the matter of two weeks (Dong et al., 2020). In response, we are also seeing states begin to pause and even reverse their reopening policies. Specifically, 11 states are reversing their reopening policies, and an additional 14 have paused their reopening plans (Lee et al., 2020).

With a resurgence in COVID-19 cases, it is inevitable that cities will go back on lock down and implement SAH orders. It is vital for policy makers to understand the mobility patterns of US residents across socioeconomic groups in order to best fit policy responses to eventually and delicately reopen the economy without causing a surge in cases.

6 Tables

Table 1: Non-pharmaceutical intervention summary statistics

NPI	Cities	Median	Max	Min
Stay at home order	29	2020-05-18	2020-06-19	2020-04-27
Nonessential business	51	2020-05-08	2020-06-05	2020-04-24
Restaurants	40	2020-05-15	2020-06-19	2020-04-27
Gyms	35	2020-05-18	2020-06-19	2020-04-24
Movie theaters	22	2020-05-14	2020-06-10	2020-04-27

Collected for all counties which removed one of the above Non-pharmaceutical interventions.

Table 2: Foot Traffic Summary Statistics

Industry	Mean	Median	Max	q.25%	q.75%	sd
Airports	666	285	7,173	22	871	1,003
Automobile repair	131	50	1,784	5	191	202
Banks and financial services	242	100	4,268	9	311	403
Bars and nightclubs	67	43	675	13	92	79
Cafes, Juice Bars, and Dessert	1,013	556	9,489	27	1,490	1,330
Full service restaurants (sit down)	2,432	314	37,520	7	3,426	4,100
Grocery stores	1,243	794	13,939	44	1,656	1,707
Gyms	417	60	8,277	13	454	805
Hotels and motels	632	438	6,265	31	881	770
Limited service restaurants (e.g. fast food)	2,030	1,038	22,230	110	3,080	2,794
Movie theaters	35	21	337	7	45	41
Other Industries	6,608	30	177,158	4	2,610	15,965
Parks and playgrounds	1,023	396	20,853	83	1,437	1,515
Sporting goods store	275	148	2,434	12	425	343
Train stations	16	10	130	4	19	19
Total visits	8,289	220	294,154	8	2,031	22,878

Notes: Industries are coded using each point of interest's NAICS code. Total visits includes every point of interest across all NAICS categories. Foot traffic data is aggregated to the county/day/industry level for each of the 51 cities of focus.

Table 3: City Summary Statistics

City	Counties	Total Visits	SAH Days	COVID Cases	Avg Vote Share	Avg Income Quantile
Albuquerque NM	4	3.0 M	NA	316.0	0.46	2.00
Atlanta GA	21	5.9 M	28	655.0	0.55	2.48
Austin TX	5	6.0 M	NA	748.0	0.47	2.60
Bakersfield CA	2	2.5 M	NA	518.0	0.61	3.00
Baltimore MD	9	3.7 M	46	1273.0	0.40	4.67
Boise ID	3	1.4 M	37	450.0	0.61	2.33
Boston MA	9	1.7 M	55	2465.0	0.37	4.22
Charlotte NC	7	5.4 M	53	1006.0	0.60	3.29
Chicago IL	11	10.7 M	69	1758.0	0.43	3.91
Cleveland OH	8	2.2 M	57	553.0	0.51	4.00
Colorado Springs CO	4	3.4 M	32	330.0	0.62	3.50
Dallas TX	9	9.2 M	NA	810.0	0.67	3.00
Denver CO	11	3.9 M	32	975.0	0.40	3.82
Detroit MI	8	2.4 M	69	1303.0	0.52	3.88
El Paso TX	4	3.2 M	NA	706.0	0.47	1.50
Fort Worth TX	2	7.1 M	NA	587.0	0.67	3.00
Fresno CA	5	2.5 M	NA	501.0	0.45	2.80
Honolulu HI	3	2.3 M	NA	66.9	0.29	3.67
Houston TX	8	20.0 M	NA	667.0	0.61	2.38
Jacksonville FL	6	7.2 M	45	648.0	0.64	2.50
Kansas City MO	7	3.9 M	28	339.0	0.52	3.43
Las Vegas NV	2	8.7 M	39	666.0	0.55	2.00
Los Angeles CA	4	7.9 M	NA	1031.0	0.36	4.00
Louisville KY	9	4.7 M	NA	509.0	0.66	3.00
Memphis TN	4	4.3 M	29	1070.0	0.54	3.00
Miami FL	6	8.2 M	45	1355.0	0.48	3.00
Milwaukee WI	5	2.6 M	49	1205.0	0.52	4.40
Minneapolis MN	9	3.3 M	51	932.0	0.47	4.78
Nashville TN	7	3.4 M	29	1413.0	0.63	3.29

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Table 3 – *Continued from previous page*

City	Counties	Total Visits	SAH Days	COVID Cases	Avg Vote Share	Avg Income Quantile
New Orleans LA	7	1.9 M	53	2012.0	0.53	2.71
New York NY	33	8.8 M	NA	2637.0	0.41	4.00
Oakland CA	2	1.2 M	NA	358.0	0.20	5.00
Oklahoma City OK	5	5.8 M	NA	365.0	0.62	3.60
Omaha NE	4	4.2 M	NA	1266.0	0.57	4.25
Philadelphia PA	12	6.8 M	65	1650.0	0.42	4.17
Phoenix AZ	1	8.0 M	46	1086.0	0.48	3.00
Portland OR	5	3.1 M	88	271.0	0.37	3.80
Raleigh NC	6	3.0 M	53	466.0	0.47	2.50
Sacramento CA	5	3.8 M	NA	208.0	0.44	4.00
Salt Lake City UT	6	2.4 M	NA	967.0	0.44	4.17
San Antonio TX	8	12.3 M	NA	603.0	0.63	2.50
San Diego CA	1	5.4 M	NA	426.0	0.37	4.00
San Francisco CA	4	2.4 M	NA	409.0	0.15	4.75
San Jose CA	1	2.8 M	NA	219.0	0.21	5.00
Seattle WA	4	2.6 M	70	453.0	0.35	4.00
Tampa FL	4	5.7 M	45	730.0	0.52	3.00
Tucson AZ	3	4.1 M	46	764.0	0.53	2.00
Tulsa OK	5	4.5 M	NA	526.0	0.70	5.00
Virginia Beach VA	11	2.7 M	60	261.0	0.42	3.64
Washington DC	12	2.6 M	58	1463.0	0.30	4.92
Wichita KS	2	3.1 M	35	244.0	0.62	3.50

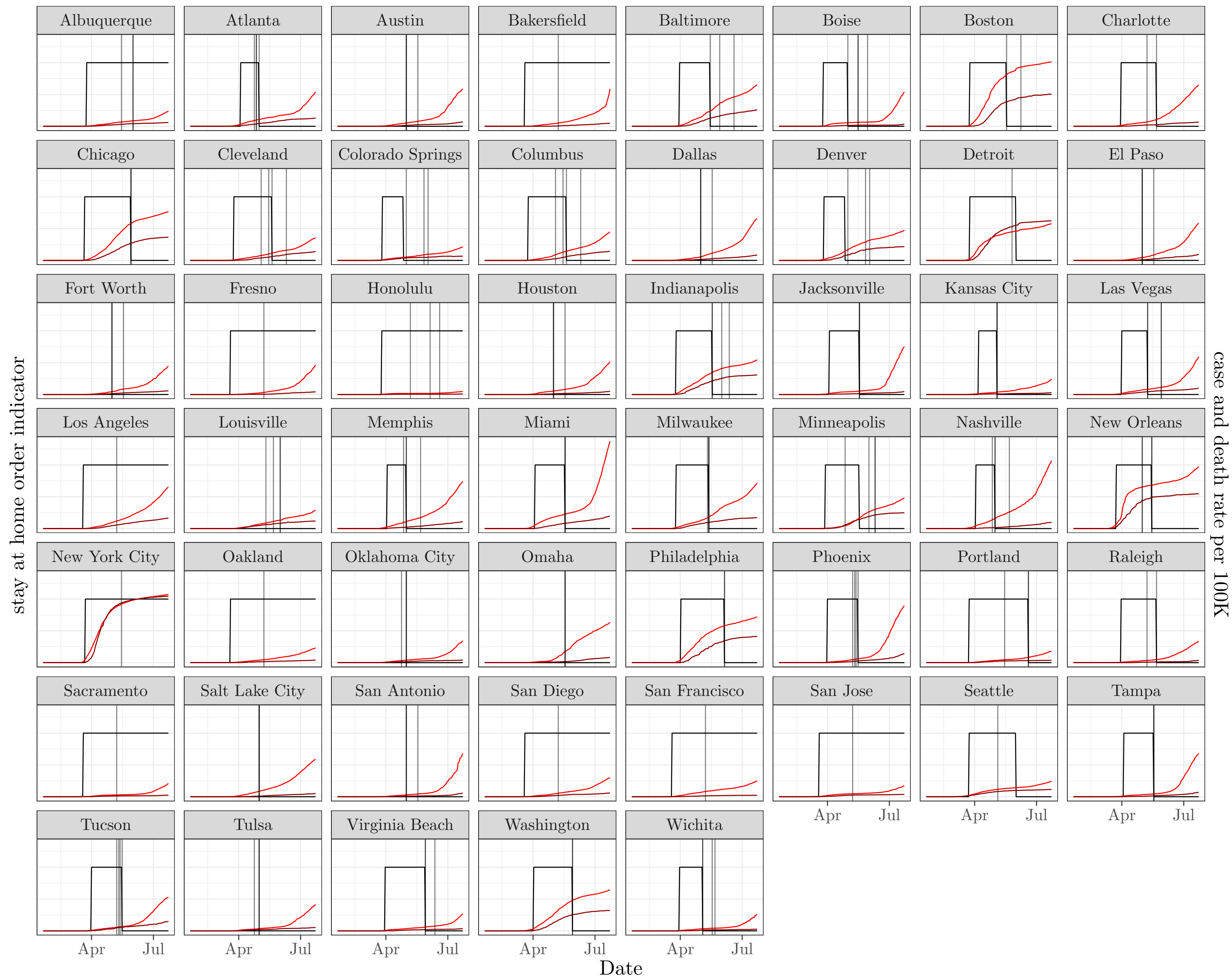
Table 4: Stay at home removal coefficients across industries

Industry	Control Group			
	SAH On	SAH Off	Unmatched data	Synthetic control*
Airports	-0.069	-0.131	-0.013	-0.119
	(0.067)	(0.143)	(0.029)	
Automobile repair	-0.008	0.303	0.130	-0.117
	(0.150)	(0.209)	(0.069)	
Banks and financial services	0.322	0.389	0.021	-0.097
	(0.135)	(0.096)	(0.038)	
Bars and nightclubs	0.146	-0.220	0.018	0.013
	(0.144)	(0.101)	(0.032)	
Cafes, Juice Bars, and Dessert	0.101	0.038	0.048	-0.018
	(0.114)	(0.099)	(0.054)	
Full service restaurants (sit down)	0.129	-0.199	-0.007	0.015
	(0.077)	(0.137)	(0.034)	
Grocery stores	-0.047	-0.337	-0.022	-0.272
	(0.300)	(0.196)	(0.097)	
Gyms	0.063	-0.078	-0.056	0.024
	(0.064)	(0.082)	(0.067)	
Hotels and motels	0.173	0.112	0.085	0.140
	(0.095)	(0.107)	(0.033)	
Limited service restaurants (e.g. fast food)	0.146	0.140	-0.064	0.008
	(0.119)	(0.104)	(0.043)	
Movie theaters	0.207	-0.054	-0.015	0.122
	(0.103)	(0.060)	(0.031)	
Parks and playgrounds	0.151	-0.070	-0.052	0.059
	(0.108)	(0.185)	(0.038)	
Sporting goods store	-0.007	-0.070	0.036	-0.009
	(0.069)	(0.193)	(0.036)	

Notes: Standard errors in parenthesis. Proper standard errors are able to be estimated following the methodology laid out in Arkhangelsky et al. (2019). At the time of writing this paper, the R package to implement these methods was in its alpha stage. See R package synthdid.

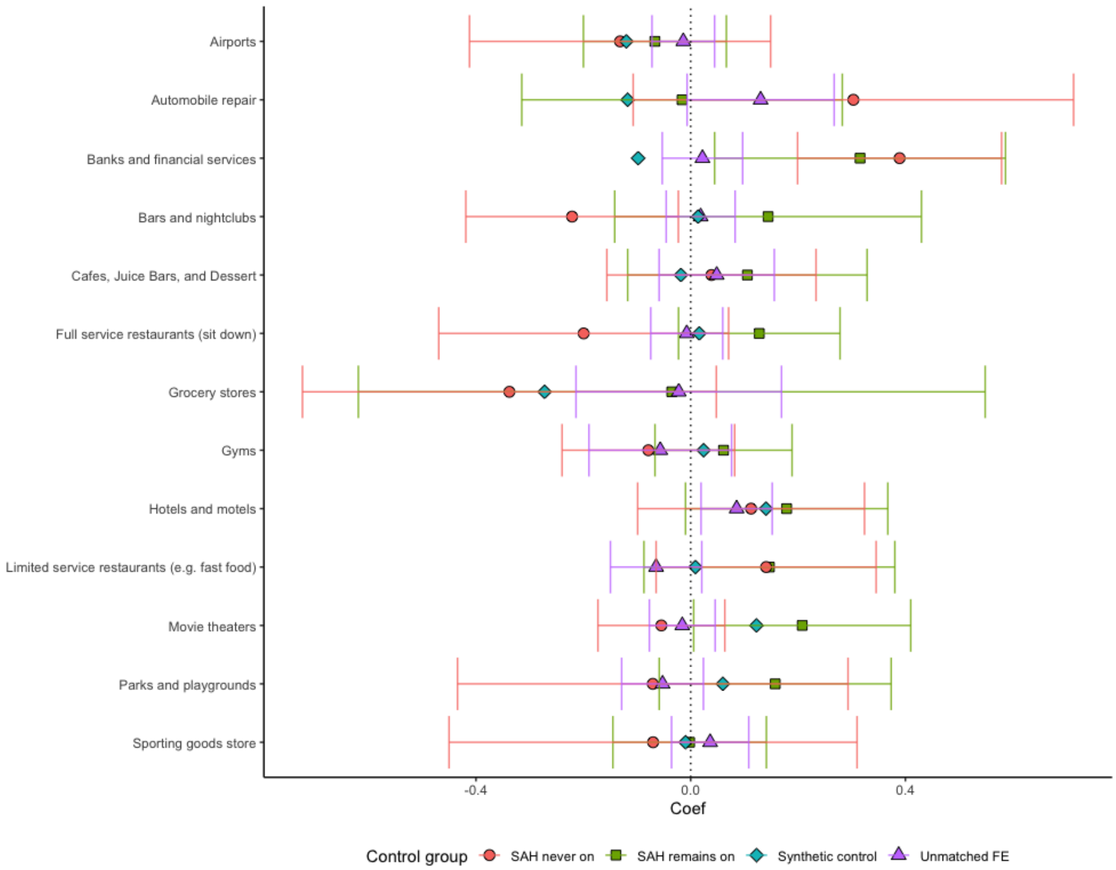
7 Figures

Figure 1: Non-pharmicitucial timeline per city



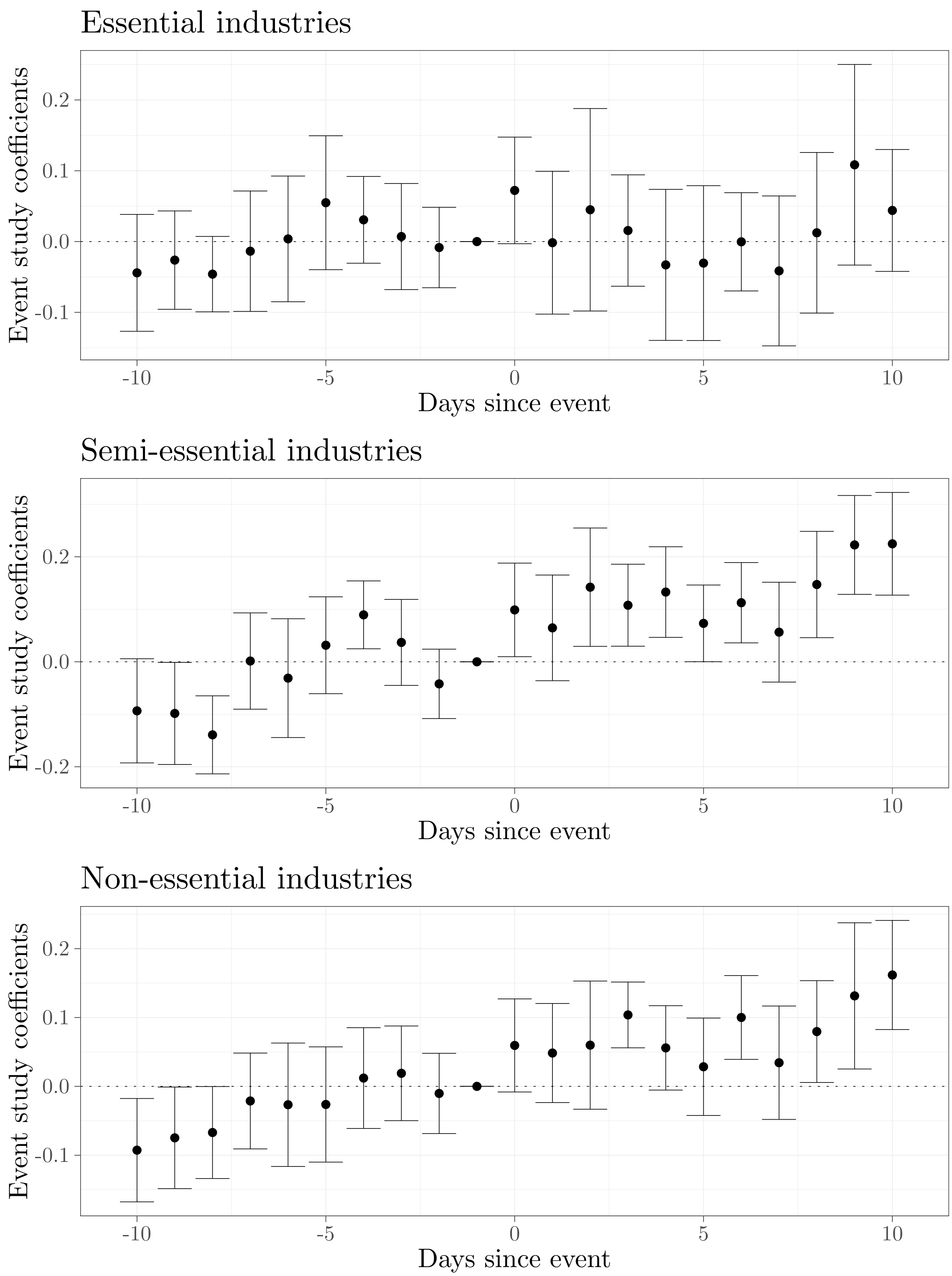
Notes: Light red lines map the COVID cases per day, dark red map the COVID deaths. The black line shows the period which each city had a stay at home order in place. The grey lines show the removal of other NPIs such as reopening restaurants, schools, movie theaters, non-essential businesses and gyms.

Figure 2: Industry regression coefficients



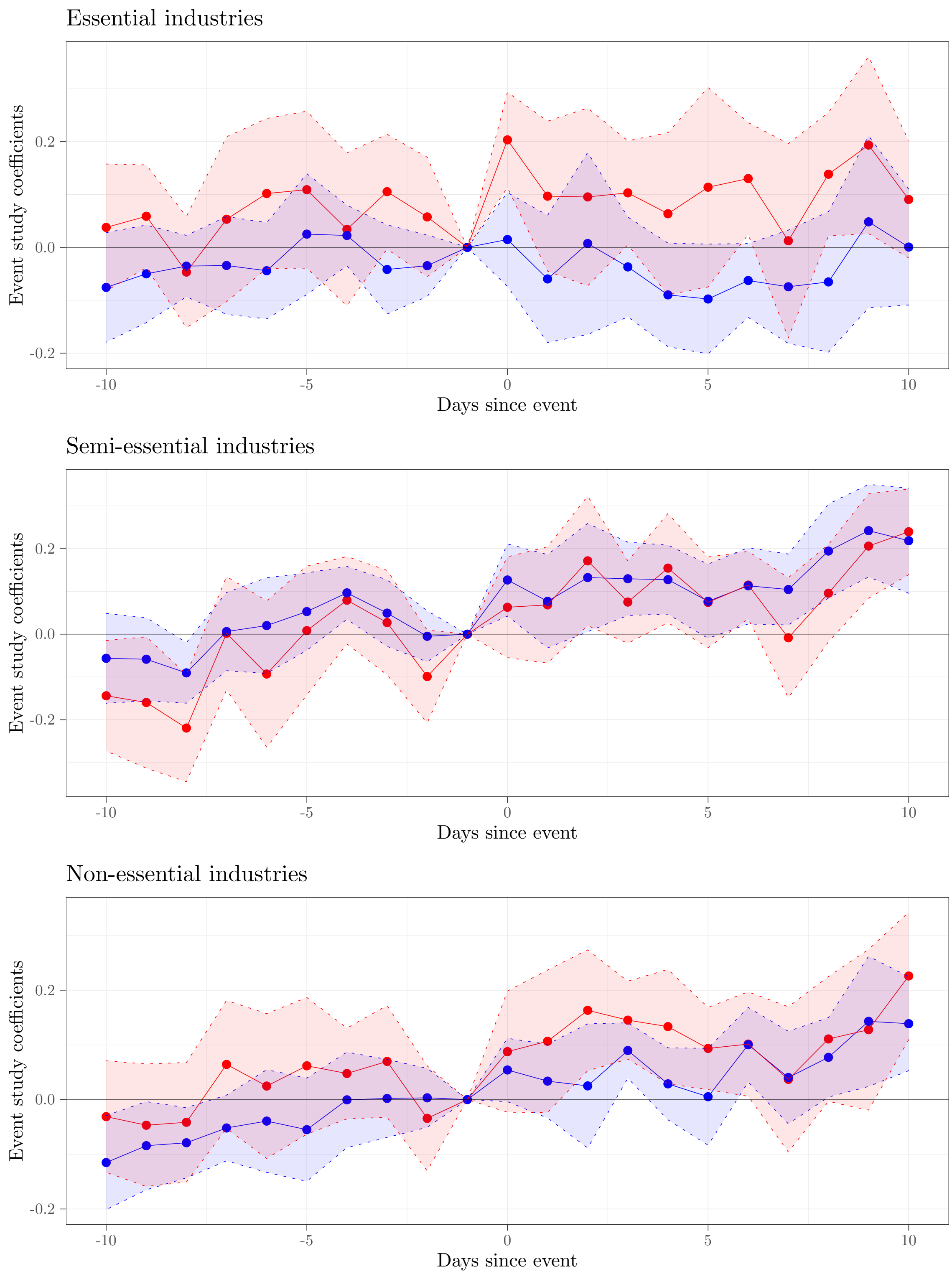
Notes: Difference-in-differences coefficients and 90% confidence intervals for each industry. Robust standard errors clustered at the state level were used with the exception of the synthetic control group where standard errors were not estimated. Points of interest were assigned industry labels based on their NAICS code.

Figure 3: Event study coefficients



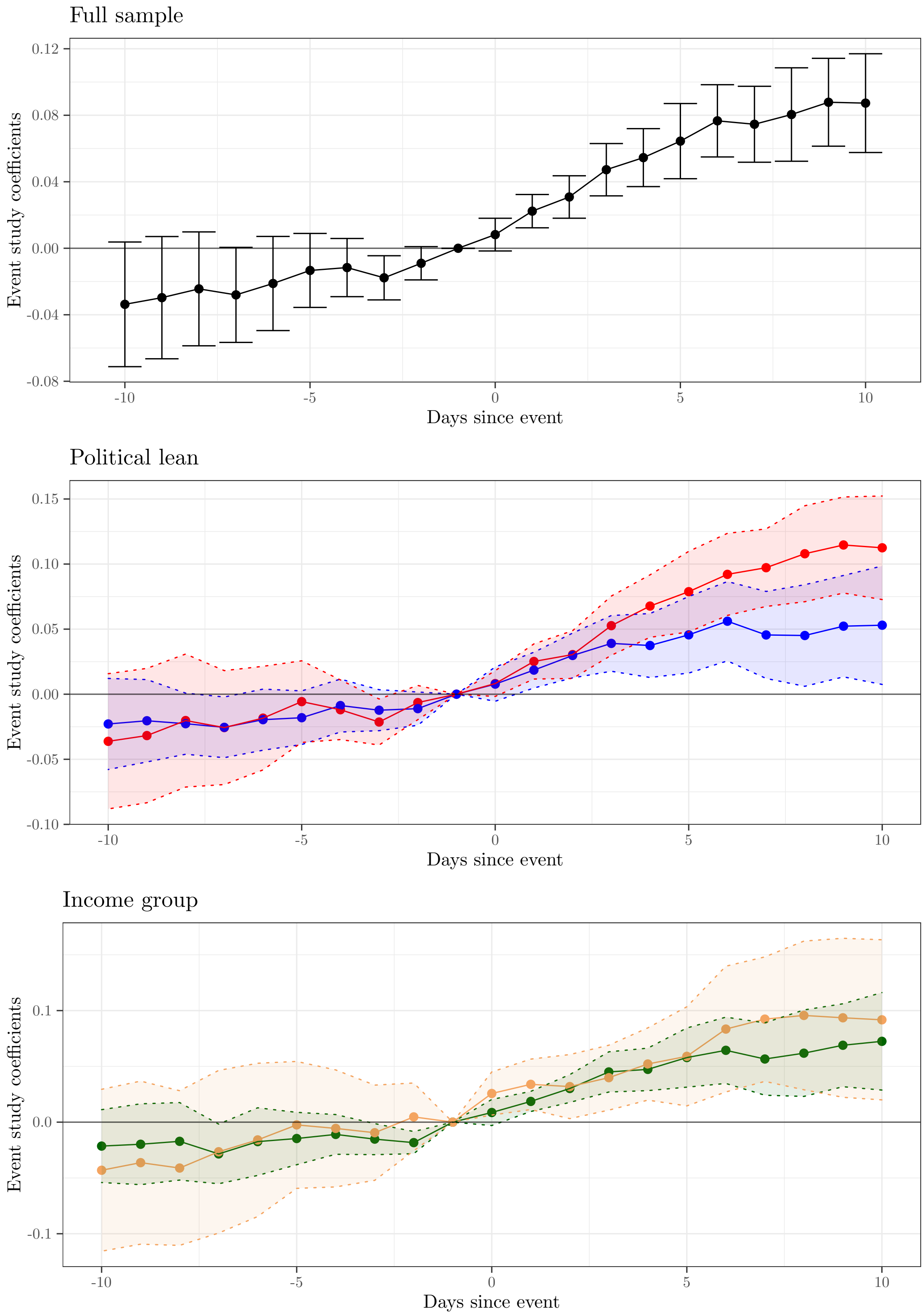
Notes: Essential industries include: Automobile repair, Banks and financial services, Grocery stores, and Train stations. Semi-essential industries include: Hotels, Parks and playgrounds, Sporting goods stores. Non-essential industries include: Bars and nightclubs, Cafes, juice bars and dessert, Full and limited service restaurants, Gyms and Movie theaters. Standard robust errors are clustered at the state level. Coefficients are presented relative to the day before the stay at home order was removed for each county.

Figure 4: Event study coefficients: Republican versus Democrat



Notes: Essential industries are composed of Automobile repair, banks and financial services, grocery stores, and train stations. Non-essential services are composed of: Bars and nightclubs, Cafes, Juice bars and dessert, Full service and limited service restaurants, gyms, and movie theaters. Semi-essential services are composed of: Hotels, Parks and playgrounds, and sporting goods stores. Standard errors are clustered at the state level. Coefficients are presented relative to one day prior to stay at home orders are removed.

Figure 5: Event study coefficients: Merchant Revenue



Notes: Revenue data for small businesses aggregated from Womply. Using same functional form. Should mention data is a 7 day moving average seasonally adjusted and indexed to January 4-31, 2020.

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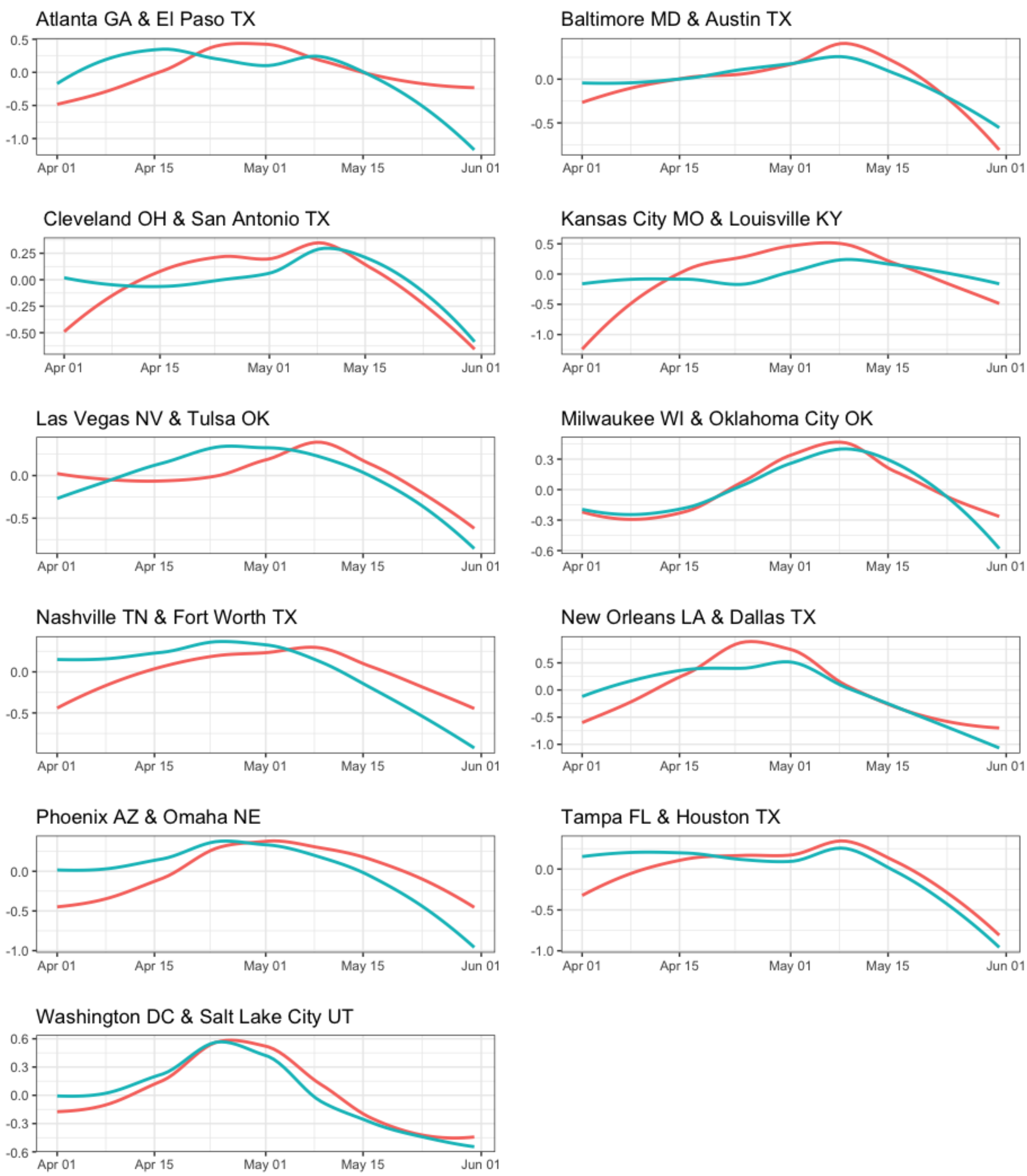
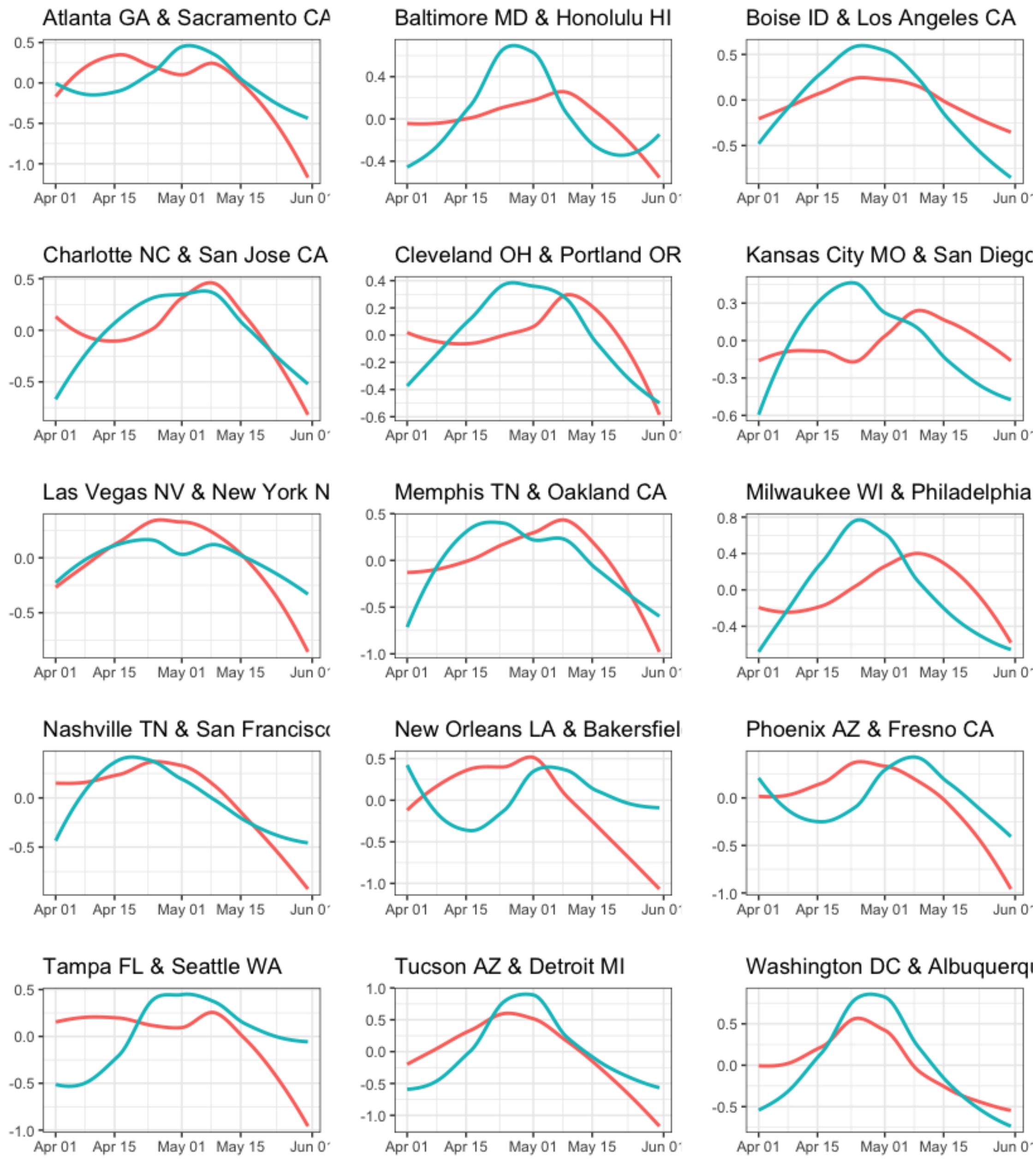
8 Appendix

Figure 6: Matched cities 2019, control group with stay at home order never in place



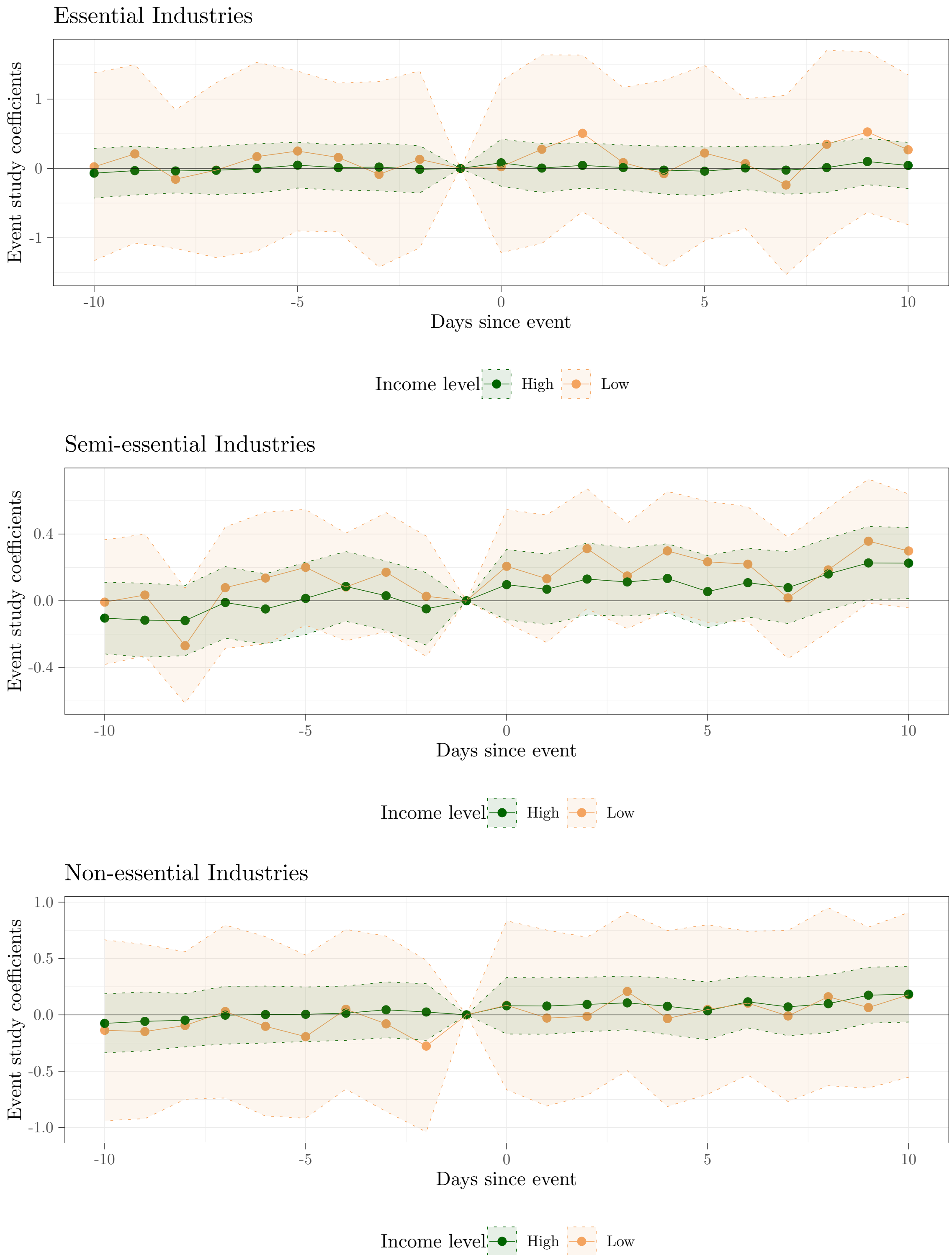
Notes: Showing standardized visits, $std\_visits = \frac{visits_{it} - \overline{visits_i}}{s_i}$

Figure 7: Matched cities 2019, control group with stay at home order still in place



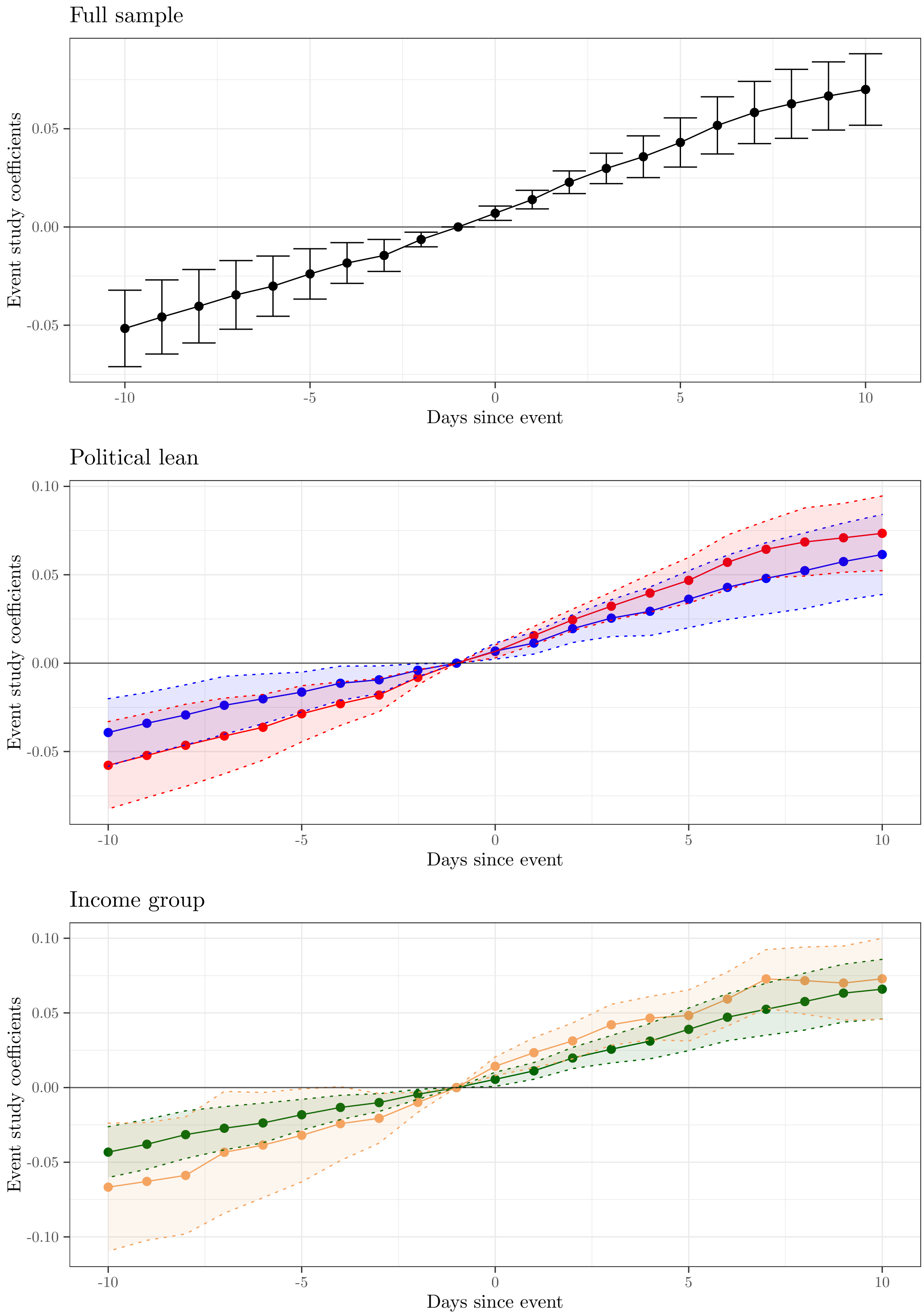
Notes: Showing standardized visits, $std\_visits = \frac{visits_{it} - \overline{visits_i}}{s_i}$

Figure 8: Event study coefficients: High income versus low income



Notes: Essential industries are composed of Automobile repair, banks and financial services, grocery stores, and train stations. Non-essential services are composed of: Bars and nightclubs, Cafes, Juice bars and dessert, Full service and limited service restaurants, gyms, and movie theaters. Semi-essential services are composed of: Hotels, Parks and playgrounds, and sporting goods stores. Standard errors are clustered at the state level. Coefficients are presented relative to one day prior to stay at home orders are removed. High and low income slices are the respective bins above and below the median decile income per county in the US.

Figure 9: Event study coefficients: Number of businesses opening



Notes: Womply merchant data. Showing the percentage change in small businesses opening. The gradual trend shows businesses are not opening in response to the stay at home orders reopening.