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Using Panel Data Analysis to Evaluate How Individual Non-Pharmaceutical Interventions Affected Traffic in the U.S. during the First Three Months of the COVID Pandemic

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Abstract: In response to the COVID-19 pandemic, restrictive non-pharmaceutical policy interventions (NPIs), with the goals of reducing interactions and travel for people in different households, were introduced. In the U.S., each state had jurisdiction over the NPI policy imposed, resulting in myriad policy decisions. The aggregate impacts of these decisions are known; however, the individual impacts are not fully understood. We disaggregated the NPIs imposed during the first three months of the epidemic (1 March and 7 June 2020) using panel data regression analysis. Vehicular travel reduction as a proxy for NPI impacts on traffic was regressed against stay-at-home orders, business closures, school closures, and gathering bans. The results show that school closures and full closures of non-essential businesses were correlated with the largest impacts in reducing vehicle trips compared to when they are not in place. Stay-at-home orders had about half the impact of school closures compared to when they were not in place. Gathering bans had the least impact. In the U.S., decisions that target businesses were the most effective in reducing vehicle traffic. There was heterogeneity in how people responded to these restrictions. This study can be used in epidemiology models and inform decision-makers on policies that work best.

Keywords: interventions policies; COVID-19 restrictions; vehicle trip reduction; heterogeneity; panel data analysis

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1. Introduction

The COVID-19 pandemic presents an interesting opportunity to evaluate how policy decisions made by elected officials affected and continue to affect travel. Since it was first reported in 2019 in Wuhan, China, the virus has spread throughout the world and is present in all of the states in the U.S. It was declared a pandemic in early 2020 [1]. The COVID-19 pandemic has had significant impacts globally on health, economies, and society as a whole [2]. Around the world, most countries implemented some form of restrictions to stem the spread of the virus. In the U.S., restrictions were made at the federal, state, and local levels. The federal-level decisions mostly influenced international travel, while state and local authorities implemented decisions at the local levels. The U.S. Center for Disease Control and Prevention (CDC) and the U.S. Department of Health and Human Services (HHS) have put in place plans to combat novel influenza pandemics. Similarly, state and local health departments for all 50 states have developed state influenza pandemic plans and guidelines. In response to COVID-19, every state governor in the U.S. implemented community mitigation measures (CMM) to restrict the movement of people and promote social distancing.

Community mitigation measures are actions that people and communities take to slow the spread of novel influenza viruses through the use of non-pharmaceutical interventions [3]. The aim of community non-pharmaceutical interventions (NPIs) is to reduce social contact between people in schools, workplaces, and other community settings. Measures that limit social contact, although not necessarily stopping the pandemic, are most effective in slowing pandemics as part of a broader comprehensive strategy incorporating other interventions. These strategies work best during the initial months from when a novel influenza virus is detected. Each U.S. state implemented a different set of community NPI policies, with different levels of enforcement and at different times as the pandemic spread. There was wider acceptance in the first few weeks of most of these NPI policies which reduced with time as their toll on society, economies, travel, and civil liberties increased. In the U.S., there are several instances where courts intervened and either reduced or overturned certain community NPIs [4].

With the scale of the impacts these measures have on economies and society, it is important to ensure that each NPI policy implemented was effective in achieving its goal of slowing the pandemic and reducing contact. These measures limit the ability of people to undertake certain out-of-home activities that generate travel demand. The amount of travel during pandemics can be used as a proxy measure to evaluate how well these NPI policies were respected. NPIs were shown to work very well to contain the spread of COVID-19 in Wuhan, China, where the measures were extreme [5]. In the U.S., these NPIs were not respected by some individuals or, in some instances, were not actively enforced. Measuring the NPI's' impacts on travel demand can be used to gauge whether they reduced social contact during the pandemic. Measuring the amount of traffic during the pandemic compared to "normal times" provides a proxy measure of how people altered their movements in response to these NPIs. The reduction in vehicular traffic does not address interactions between members of different households that resulted in increased infections. However, given that travel demand is derived demand, travel reductions measure how people responded to restrictions such as NPI policy measures. Additionally, we consider only vehicle passenger trips due to the availability of the data. Vehicle passenger trips make up 87.5% [6] of total trips in the U.S. in 2020 and provide a good measure of how people reduced their trips due to the COVID pandemic. Although the cumulative impacts of the NPI policies on travel reduction have been evaluated in the literature, the individual impacts have not been appropriately evaluated in the literature; for example, which of these measures were most correlated to reducing travel during the start of the pandemic compared to when they were not in place. Separating the cumulative NPIs into individual effects is even more important to ensure that the best policy tools are used to fight future pandemics.

1.1. Review of the Impacts of Pandemics and NPI Policies on Travel Demand

The literature measuring the effectiveness of travel-related measures on the spread of pandemics can be divided based on the methods used, mainly observational and modeling/experimental studies. Observational studies are studies that used empirical data for analyzing the pandemic's impacts on travel, see for example [7–13]. Modeling and experimental studies use computer models or experiments to evaluate the impacts of pandemics on travel [14–19]. We present a limited synopsis of this literature to construct the framework for the analysis of this study.

Several reports and big data aggregators documented the impacts of COVID-19 on travel. Google [1], Inrix Inc. [2] Streetlight Data [2] all evaluated the impacts of COVID-19 NPI policy impacts on travel at various geographical scales using different measurements, and for different purposes. All of these big data sources show that traffic reduced significantly at the initial peak of the COVID-19 pandemic in the U.S. between 1 March and 7 June 2020. U.S. Travel slowly picked up in the summer of 2020 as these community NPIs were relaxed, people became fatigued, the risk perception of getting COVID waned, and more information about the COVID-19 flu virus was known [20]

Some published studies have evaluated the impacts of COVID-19 on travel through empirical analysis. In Colombia, the short-term impacts of COVID-19 government measures were evaluated using official and secondary data for the most populated cities in the country [21]. Three components of the transportation system were evaluated—air, freight, and urban transport systems. Several NPIs were issued in Colombia during the data period used in the study. The study compared the data with data from the same periods for 2019 and found that travel reduced significantly for all three components. The study did not disaggregate the impacts of individual NPI effects.

A study in Italy evaluated the urban traffic volumes and noise emissions in Rome in the context of the COVID-19 pandemic containment measures [22]. They used simulations to obtain traffic volumes which were then inputted into a noise assessment simulation model. Their results indicated a significant aggregate reduction in traffic with a subsequent increase in travel speed and a reduction in noise pollution. Using paired T-test statistics, traffic volumes on roadways were compared between a base period and periods when the COVID-19 NPI measures were first instituted in Florida, USA [23]. The study indicated that traffic volume and roadways dropped by over 47.5% on average. Other studies looked at the impact of travel restrictions on the transmission of COVID-19 infection [24–26].

Other studies conducted surveys to estimate how travel changed during and after the initial implementations of NPIs. Longitudinal travel and activity surveys were conducted in Australia to analyze the impacts of travel restrictions on travel demand activity. Their study indicated that respondents were becoming more comfortable with reducing social distancing restrictions. Aggregate travel increased by over 50% in comparison to initial restrictions. Vehicle travel rebounded better than other modes. Another study used expert surveys to evaluate the long-term impacts and uncertainties of COVID-19 on the transport sector [27]. They interviewed experts from all continents across the world. Their study indicated that working from home will become more prevalent compared to pre-COVID-19 periods and vehicle traffic will also become more prevalent.

The impacts of NPIs were empirically estimated relative to the number of new cases attributed to each NPI on a cross-country basis [28]. The research evaluated NPIs in 20 countries, including the U.S., using a Bayesian hierarchical model. The results indicated that bans of large gatherings were the most effective, followed by venue closures, whereas stay-at-home orders and working from home were least effective. The main limitation of this study is that it assumes that NPIs are instituted at the Federal or national level. This is not the case in the U.S. where each state introduced its NPI. The results for the U.S. could thus be biased.

The literature review shows that the aggregate pandemic NPI effects on travel demand are well understood. Since most of these NPIs were instituted at the same time, it is important to identify the individual effects to evaluate their efficacy in reducing travel during pandemics, given their potential to slow pandemics and their impacts on economies and society.

1.2. Objectives

The main objective of this study was to deconstruct and quantify the vehicular travel impacts of the policy NPIs instituted in each state due to COVID-19 into their individual effects during the initial months of the pandemic in the U.S. This study uses data for the initial three months (March and early June 2020) when COVID-19 became endemic/pandemic in the U.S. These initial months are identified by the U.S. Department of HHS as the critical months that could determine how widespread a novel influenza virus will be [3]. A secondary objective was to evaluate whether there was heterogeneity in how citizens responded to the NPIs across different states. The overall goal of this study was to evaluate how well U.S. Citizens responded to each of the NPI policies using the proxy measure of vehicular traffic in the U.S. during the initial stages of the pandemic. Since the goals of these NPI policies are to increase social distancing, measuring the amount of travel when they are in place may provide some measure of how well citizens respect them.

There are two main limitations to this study. First, this research does not address the spread/exposure to COVID-19 when these policies were in place. Additionally, we only considered restrictions that were made state-wide; some localities and municipalities implemented more stringent NPI policies at different times during the initial stages of the pandemic.

Secondly, this research uses only vehicular data as a proxy for measuring travel. In addition to the NPIs that were instituted, some transit users and U.S. travelers switched their modes from public transport to private vehicles to protect themselves from COVID-19 exposure. A study showed that 74.5% of transit users used transit less due to infection risks in public transit, and transit service changes at the height of the pandemic in the U.S. [29]. Although there was a reduction in private vehicle traffic overall, there is a potential percentage increase in vehicle traffic due to modal shifts from transit which is not modeled. The percentage of transit use and other modes is significantly low compared to vehicle transport and may not significantly impact the results. Additionally, air travel is not addressed.

2. Materials and Methods

We posit that reductions in vehicular traffic during the COVID-19 pandemic were strongly correlated with NPI policy decisions. Additionally, local time-invariant characteristics, enforcement strategies, and beliefs impacted how citizens in each state responded to these NPIs. The implication is that there is unobserved heterogeneity between states in how citizens responded to NPI policies.

To test our hypotheses and evaluate how these NPIs affected the reduction in travel, we used travel demand variables as the dependent variable in a panel data analysis. COVID-19-related NPI decisions by elected officials at the state level were used as the explanatory variables to estimate the impacts of each of the NPI policy decisions. The choice of explanatory variables is based on theory, reports of COVID-19, and a review of the various decisions that were being made by different decision-makers when COVID-19 became endemic in the U.S.

In addition to the NPI decision variables, we also included other variables related to COVID-19 severity, including deaths and new cases. We tested several variables using different functional forms for their significance in predicting travel reduction. However, our final model includes only independent variables that were significant in predicting the reduction in travel. We hypothesize that in addition to the direct relationship between our dependent and independent variables, there are local cultural and political influences that determine how citizens within each state responded to the decisions made by their leaders to reduce their travel. Our conceptual framework is based on this hypothesis and decisions that restrict the movement of individuals affecting the amount of travel that is made within each geography.

The relationships described can be modeled best using panel data analysis (PDA). Using PDA, we can model the relationship between traffic reduction using daily data, for each state over the first three months of the pandemic. Our research focuses on vehicle travel since the data was readily available at the scale, geographies, and periods used in this study. Given that measurable NPIs were made and implemented statewide at the time, states are used for the spatial unit in this study. The model was estimated for all 50 U.S. states between 1 March and 7 June 2020. The first three months are chosen because the initial months of a pandemic are critical in preventing its spread.

2.1. Dependent Variable

The dependent variable used in this research is the normalized daily number of vehicle trips (NDTs) for each state and each date in the data collection period. Daily vehicle trips measure the number of vehicle trips that are made each day. Comparing the trips during the first three months when COVID-19 NPI policies were introduced in the U.S. to normal trips that would have occurred without COVID-19 and the NPI policies provides

a metric that showed how trips changed due to these policies. Daily vehicle trips during the data collection period were thus normalized and seasonally adjusted and used as the dependent variable. The NDTs are a ratio with values below one indicating that trips were lower compared to what they should have been and values above one indicating that trips were higher than normal during the data collection period. The data were obtained from a private big data source INRIX Inc. using their Trip Trends dataset [30]. INRIX Trip Trends summarizes the travel data for various regions around the world and was developed to help decision-makers keep track of the rate and distribution of travel during the COVID-19 pandemic.

Table 1 shows the descriptive statistics for the dependent variables for each state in the U.S. for the data collection period. It shows that on average, the U.S. saw a 30% reduction in NDTs for the data collection period.

Table 1. Descriptive Statistics of Dependent Variable Data (4950 Observations).

Variable	Mean	Standard Deviation	Minimum	Maximum
Normalized Daily Vehicle Trips	0.70	0.17	0.29	1.18

2.2. Explanatory Variables

The explanatory variables used in this research are grouped into NPI policy variables and weekday/weekend days. For the NPI policy variables, data were collected online through each State Governor's official website. All the declarations made by each state governor regarding COVID-19 were collated and then transcribed to reflect whether that decision was an NPI variable or not. Data included declarations of stay-at-home orders, for example, how long they were instituted for and when those orders were rescinded, if at all. We discuss the explanatory variables further in the next subsections.

2.2.1. Non-Pharmaceutical Intervention COVID-19 Variables (NPI Variables)

NPI variable data were collected from each of the state governors' websites and grouped into stay-at-home orders (SAHO), gathering bans (GB), non-essential business closures (NEBC), and school closures (SC). The variables were all indicator variables showing whether an order was in place or not for a particular day for each state.

Stay-at-home orders required residents to stay at home except for essential business. The first stay-at-home order in the U.S. was issued by six bay-area communities in the state of California on March 16th. The first statewide order was issued by Governor Newsom of California. Five states, Arkansas, Iowa, Nebraska, North Dakota, and South Dakota did not issue SAHO. The SAHO variable was an indicator variable with a one or zero indicating whether it was in place for a particular day or not.

Gathering bans (GB) are broadly defined as bans on events convening a certain number of people from different households into a single room or single space at a time. In the U.S. they ranged from bans of 5 or more people to up to bans of 250 people during the data collection period. Gathering bans have been shown in the literature to be significant in reducing pandemics [4,31,32]. Because of the range of gathering limitations, as long as a state issued a gathering ban, regardless of the size of the ban, we considered the state to have a gathering ban. GB was also an indicator variable, with one for when it was in place and zero otherwise.

Non-essential business closures were issued by all states at varying levels. Some studies have shown these closures moderately affect influenza transmissions but are associated with high societal costs [17,33]. Some businesses in different states were considered non-essential, whereas in other states, they were considered essential. For example, some states considered churches and places of worship as essential businesses while others did not consider them to be essential. Healthcare and grocery stores were considered essential businesses for all the states. Overall, all states had some form of a nonessential business closure. This variable was further disaggregated into two variables: Full ban, where non-essential

businesses were fully closed (NEBC1); and partial bans (NEBC2), where businesses were opened but not at full capacity. Capacity restrictions for NEBC2 ranged from 25% to 75% of full capacities. NEBC1 and NEBC2 were both indicator variables, with one for when they were in place, and zero otherwise.

School closures referred to the closing of K-12 schools in-class instructions. School closures were modeled as indicator variables with one being closed, and zero otherwise. Several studies have evaluated the impacts of school closures on the spread of pandemics showing that they had significant impacts on reducing pandemics [18,34–36]]. School closures had a direct and indirect impact on traffic reduction. Directly, the trips that were made to schools by students and their parents to drop them off, teachers and other school staff going to work, and businesses that serviced these schools. Indirectly, because kids had to stay at home, some parents who could not afford daycare or leave their young kids at home had to stay at home to take care of their kids. Additionally, after-school programs, camps, and playgrounds that kids could go to were also closed resulting in a further reduction in trips. Table 2 shows the descriptive statistics for the NPI policy variables used in this study. The statistics show the proportion of the time during the data collection period that a particular NPI policy was in place. School closure had the highest proportion of time in comparison to the other variables. This is intuitive as school closures were one of the first NPI policies instituted by state governors and lasted throughout the data collection period. Overall, schools were closed for 83%, gathering bans for 63%, non-essential business closures for 56%, and stay-at-home orders for 43% of the time during the data collection period.

Table 2. Descriptive Statistics of Explanatory NPI Variables.

Variable	Means and Proportions	Standard Deviation	Minimum	Maximum
Stay-at-home-orders	0.43	0.50	0.00	1.00
Gathering Ban	0.63	0.48	0.00	1.00
School Closure	0.83	0.38	0.00	1.00
Non-essential Business Closures	0.56	0.50	0.00	1.00
Partial Non-essential Business Closures	0.25	0.43	0.00	1.00

2.2.2. Week-Day vs. Weekend Day Variable

The data also showed fluctuations and patterns that repeat themselves based on the day of the week. The day of the week was used to account for typical variations in traffic that occur on weekdays and weekend days. The data also showed fluctuations and patterns that repeat themselves based on the day of the week. The days of the week are modeled as indicator variables as weekdays—Monday through Thursday (MTWTR)—and weekend days (Friday through Sunday) showing the proportion of days for the data. Trip patterns for weekdays are similar and are different from trip patterns over the weekends.

2.3. Theoretical Model

Since the data had cross-sectional and temporal dimensions, panel data analysis was appropriate for this study. The spatial components relate to the unit of analysis—the 50 states and the temporal components which are daily. As mentioned previously, we posit that each state had local specific and time-invariant factors that influence the NDT which are also correlated with the independent variables resulting in heterogeneity since they are either not measured or omitted. These could include political, social, cultural, and local beliefs that do not change over such a short time that influenced both the policy decisions made by the leaders and the amount of travel that residents made. Thus, the pooled OLS model will be biased. The selection of an appropriate model to account for its heterogeneity is important. The panel data regression models are discussed next.

Panel Data Regression Model Formulation

Panel data analyses are motivated by longitudinal or cross-sectional time-series data for which data are collected for individual units over several periods. Panel data analysis provides the flexibility of modeling differences in behaviors across individuals over time. The error components in panel data analysis play an important role in the model specification. The error structure can be one or two-way depending on whether we hypothesize that the error term is cross-sectional or time-series, and, or both. For our analysis, we assume that we have time-invariant group characteristics and thus the one-way cross-sectional formulation is appropriate. The formulation for the error structure for the one-way model is [8]:

$$\varepsilon_{it} = \mu_i + v_{it}$$

where μ_i is the unobservable group-specific time-invariant effect and accounts for the terms that are not included in the model. μ_i encapsulates all of the variables that affect the dependent variable cross-sectionally but are time-invariant. μ_i enables us to capture heterogeneity by allowing for different intercepts across each cross-sectional unit. v_{it} is the remaining error term that varies cross-sectionally and across time similar to error terms in regression analysis. There are three basic formulations for panel data analysis: pooled model, fixed-effects model, and random-effects model. The basic framework for panel data is formulated as [8]:

$$Y_{it} = x'_{it}\beta + z'_i\alpha + \varepsilon_{it} = x'_{it}\beta + c_i + \varepsilon_{it}$$

where, Y_{it} is the dependent variable (NDT), x'_{it} are the independent variables; $z'_i\alpha$ contains heterogeneity or individual effects. To estimate the model efficiently, z_i is a constant term that consists of two components. These include time-invariant observed but omitted variables, such as the political leanings of each state, and time-invariant group-specific unobserved and omitted variables, such as local cultures and beliefs. If z_i is observed for all the groups, then the model is reduced to an OLS model and can be fit using least squares—pooled regression [37].

The pooled model is very restrictive and ignores the time-dependent components and assumes there is no heterogeneity. If z_i is unobserved and correlated with x'_{it}, then the OLS estimate becomes biased and inconsistent. The functional form of the Fixed -Effect Model (FE Model) is formulated as [8]:

$$Y_{it} = (\alpha + u_i) + X'_{it}\beta + \varepsilon_{it}$$

εit is a classical disturbance with $E[\varepsilon it \mid \text{xit}] = 0$ and $\text{Var}[\varepsilon it \mid \text{xit}] = \sigma_t^2$

For our study, individual state characteristics such as local beliefs or cultures that are not measured will influence how residents in a state respond to the COVID-19 NPI policies. The heterogeneity in u_i is captured by allowing different intercepts for each cross-sectional unit (states). If the unobserved group-specific effects are assumed to be random and uncorrelated with the other regressors, then the REM model is efficient and consistent. The model was estimated using the Least-squares dummy variable regression.

The REM model is formulated as [37]:

$$Y_{it} = \alpha + x'_{it}\beta + (u_i + \varepsilon_{it})$$

This model is a linear regression model with a compound disturbance that will have an inefficient estimate if the pooled OLS is used. The RE model assumes that individual effects are uncorrelated with any regressors and that the variance error estimates are specific to the groups. Hence the group-specific effects are distributed independently of the regressors. The main difference between the FE Model and RE Model is that individual-specific effects are correlated with the regressors for FE Model and are not for the RE Model. If they are correlated, the FE model is both efficient and consistent; otherwise, the REM is consistent and efficient. The RE model was estimated by the generalized least square regression method. The models were estimated using N-Logit software.

3. Results

We tested non-linear models, interaction terms between the different variables, and two-way FE models. The interaction terms were all insignificant and the two-way models were inconsistent and biased. For brevity, we report only the results of the model output with robust results.

3.1. Goodness-of-Fit Measures

3.1.1. Tests for Multicollinearity

There is a possibility of multicollinearity since some of the NPIs were introduced simultaneously during the data collection period. To test for multicollinearity, variance inflation factors (VIFs) were calculated. Variance inflation factors quantify the extent of correlation between each predictor variable and the other predictors in the model. Some authors suggest that values above 10 are problematic [38,39]. Table 3 reports the VIFs for this study. All VIFs are less than 5, suggesting that multicollinearity was not problematic.

Table 3. Variance Inflation Factors.

Explanatory Variable	VIF
Stay-at-home orders	1.72817
Gathering Bans	2.0455
Full Non-Essential Business Closure	2.08624
Partial Non-Essential Business Closure	3.79808
School closures	3.00326

Additionally, the Pearson correlation coefficients between the explanatory variables are shown in Table 4. The coefficients indicate the strength of linear relationships that might exist between two variables. Full non-essential business closures (NEBC) and partial non-essential businesses have the highest correlations at −0.65. This result showed that as Full business closures were inversely related to partial business closures as expected. Additionally, stay-at-home orders and gathering bans had a negative correlation with partial business closures. This was also an indication that as SAHO and GB were being relaxed, most states were moving from full non-essential business to partial non-essential business closures. In general, absolute correlation coefficients of >0.7 among two predictors indicate the presence of multicollinearity. Tables 3 and 4 thus indicate that the model does not have a significant multicollinearity problem.

Table 4. Pearson correlations between explanatory variables.

	SAHO	GB	NEBC1	NEBC2	SC
SAHO	1.000				
GB	0.595	1.000			
NEBC1	0.569	0.631	1.000		
NEBC2	−0.326	−0.329	−0.651	1.000	
SC	0.368	0.466	0.391	0.215	1.000

3.1.2. Pooled OLS Regression Model vs. Fixed-Effects Models vs. Random-Effects Model Goodness of Fit Measure

To determine the Best Linear Unbiased Estimator (BLUE)for the data, the pooled OLS, FE, and RE models were estimated and compared using goodness of fit measures.

Fixed-Effect Model

To test whether the pooled OLS model or the random-effects model was the BLUE, four classical models were estimated. The null hypothesis was that all the state-specific effects are jointly equal to zero, implying that there is no fixed effect in the dataset. The pooled regression model treats the panel data as if it were a single cross-sectional data. Thus, if we fail to reject the null hypothesis, then the pooled regression model is the best fit model for the data. The four classical models estimated are shown in the following empirical equations:

$$NDT_{it} = \alpha + \varepsilon_{it} \text{ (Constant term only—Model 1)}$$
$$NDT_{it} = \alpha_i + \varepsilon_{it} \text{ (group effects only—Model 2)}$$
$$NDT_{it} = \alpha + SAHO_{it}\beta_1 + SC_{it}\beta_2 + NEBC1_{it}\beta_3 + NEBC2_{it}\beta_4 + MTWT_{it}\beta_5 + GB_{it}\beta_6 + \varepsilon_{it}$$
(Regressors only—pooled regression—Model 3)
$NDT_{it} = \alpha_i + u_i s_i + SAHO_{it}\beta_1 + SC_{it}\beta_2 + NEBC1_{it}\beta_3 + NEBC2_{it}\beta_4 + MTWT_{it}\beta_5 + GB_{it}\beta_6 + \varepsilon_{it}$ (Regressors and group effects—FE Model, Model 4)

where,

α_i = is a fixed or random effect specific to an individual (group)
NDT_{it} = Normalized Daily Trips for State i at time t;
$SAHO_{it}$ = stay-at-home-Order indicator variable for state i at time t, 1 if it was in place 0 otherwise;
SC_{it} = school closure indicator variable for state i at time t, 1 if it was in place 0 otherwise;
$NEBC1_{it}$ = full non-essential business closure indicator variable for state i at time t, 1 if it was in place 0 otherwise;
$NEBC2_{it}$ = partial non-essential business closure indicator variable for state i at time t, 1 if it was in place 0 otherwise;
s_i = group dummy variables for each state;
u_i = are the respective parameter estimates for the group dummy variables.

The fixed-effect modes are estimated using the least squares dummy variable method [37]. The test statistics for Models 1–4 are reported in Table 5 including the log-likelihood function, the sum of squared residuals, and the R-squared values (See [37] for the technical details of the estimations). The results of the log-likelihood, sum of squares of the residuals, and R-squared values indicate that Model 4 the FE model best fits the data.

Table 5. Test Statistics for the Pooled and FE Models.

Model	Description	Log-Likelihood	Sum of Squares	R-Squared
1	Constant term only	1692.46793	146.26797	0
2	Group effects only	2104.22881	123.85015	0.15327
3	Regressors Only	4261.63014	51.80025	0.64585
4	Regressors and group effects	5338.07286	33.53094	0.77076

The results for the null hypothesis, that there are no fixed effects, are reported in Table 5. The Chi-square statistics, based on the likelihood functions, and F Statistics, based on the sum of the squares, are used to test for several restrictions and hypotheses defined as:

(2) vs. (1): tests Model 1 as a restriction on Model 2, i.e., there are no group effects on the mean of the dependent variable;

(3) vs. (1): tests Model 1 as a restriction on Model 3, i.e., there is no fit in the regression of NDT on the regressors only;

(4) vs. (1): tests Model 1 as a restriction on Model 4, i.e., no group effects or fit in the regression;

(4) vs. (2): tests Model 2 as a restriction on Model 4 i.e., there are group effects but no fit in the regression;

(4) vs. (3): tests Model 3 as a restriction on Model 4 i.e., there is a fit in the regression but no group effects.

Based on the Chi-squared statistic (p-values < 0.00) and F-test statistic (p-values all <0.000) shown in Table 6, we reject the null hypothesis that all state-specific effects are jointly zero. Thus, the FE model is the BLUE model in comparison to the pooled OLS model.

Table 6. Hypothesis Test for the Null Model with no Fixed Effects vs. Fixed Effects.

	Likelihood Ratio Tests			F Tests			
Test Restriction	**Chi-Squared**	**d.f.**	**Prob**	**F**	**d.f**	**Denominator**	***p* Value**
(2) vs. (1)	823.52	49	0.0000	18.10	49	4900.00	0.0000
(3) vs. (1)	5138.32	6	0.0000	1502.42	6	4943.00	0.0000
(4) vs. (1)	7291.21	55	0.0000	299.17	55	4894.00	0.0000
(4) vs. (2)	6467.69	6	0.0000	2197.09	6	4894.00	0.0000
(4) vs. (3)	2152.89	49	0.0000	54.42	49	4894.00	0.0000

Random-Effects Model

A random-effect model was also fitted to evaluate whether it fits the data. The empirical RE model estimated is shown in the following equation:

$$NDT_{it} = \alpha + SAHO_{it}\beta_1 + SC_{it}\beta_2 + NEBC1_{it}\beta_3 + NEBC2_{it}\beta_4 + MTWT_{it}\beta_5 + \varepsilon_{it}$$

where,

α = is the constant term,
ε_{it} = is a composite error term,
all other variables were defined previously.

The Breusch-Pagan (B-P) Lagrange Multiplier (LM) chi test statistics were used to examine if random effects exist. The null hypothesis was that state-specific error variance components were zero with the alternative that they are not. If we fail to reject the null hypothesis, then the pooled OLS model fits the data better than the random-effects model. With the large B-P test Chi-squared value 27,450.09822, we reject the null hypothesis in favor of the RE model (p < 0.000). Thus, the RE model fits the data better than the pooled OLS model.

Test for Best Linear Unbiased Estimator (BLUE) between Fixed- and Random-Effects Models

Since both null hypotheses, F-test for the FE model and the LM test for the RE model, were rejected, the Hausman Specification test was used to compare the FE and RE models [37,40]. The Hausman specification test tests the null hypothesis that individual effects are uncorrelated with other regressors in the model, the alternative hypothesis being that they are not correlated. The Hausman test statistic was 23.89 (p-value = 0.002389, <0.05), and the null hypothesis is rejected. Thus, the FE model was the BLUE, and was consistent. This confirms our hypothesis that there were fixed group effects and the presence of unobserved heterogeneity between states in how citizens responded to NPI policy decisions made by their state governors. The implication is that the change in daily trips for similar NPI policies is different for different states.

3.2. Empirical Results

Table 7 shows the model parameter estimates for the fixed- and random-effects models. All the independent variables were significant at the 0.01 significance level. We discuss only the FE model results, as it is the BLUE. The parameter estimates for all the NPI variables were negative confirming that their implementation resulted in a reduction in

Normalized Daily Trips during the first three months of the COVID-19 pandemic in the U.S. The variables are all indicator variables, the parameter estimates show how much each variable reduced/increased NDT in comparison to when they were not in place.

Table 7. FEM and REM Parameter Estimates.

	Fixed-Effects Model	**Random-Effects Model**
Stay-at-Home-Orders	−0.07850 ***	−0.07908 ***
	(0.00361)	(0.00359)
Gathering Bans	0.01656 ***	−0.01609 ***
	(0.00409)	(0.00408)
School Closures	−0.16651 ***	−0.16621 ***
	(0.00546)	(0.00544)
Full Non-Essential Business Closures	−0.15626 ***	−0.15626 ***
	(0.00514)	(0.00513)
Partial Non-Essential Business Closures	−0.08164 ***	−0.08185 ***
	(0.0054)	(0.00539)
Week-Day	0.00732 ***	0.00733 ***
	(0.00237)	(0.00237)
Constant		0.98269 ***
		(0.00914)
F Test (Model)	299.1728	1502
DF	55	5
R-square	0.77076	0.64192
Hausman Test	23.89	
N	4950	4950

Note: ***, **, * ≥ Significance at 1%, 5%, 10% level.

4. Discussion

Overall, school closures were correlated with the highest reduction in NDT compared to when they were not in place (16.7% reduction). School closure for this model included only K-12 schools and not colleges or daycare centers. School closure reduced traffic directly by reducing trips to schools by students, teachers, and other service providers. Additionally, parents who had young kids had to stay at home to take care of these kids due to the closures of daycares. According to the National Household Travel Survey (NHTS), about 50% of K-12 school trips occurred by auto; the rest occurred using other modes [9]. Only these trips are potentially captured in this study. Consideration of other modes will provide a better picture of the effectiveness of school closures as an NPI policy during the first months of an influenza pandemic.

Full Non-Essential Business Closures were correlated with approximately a 15.6% reduction in NDT compared to when they were not in place. Partial Non-Essential business closures were correlated with an 8.2% reduction in traffic compared to when they are not in place. As the pandemic progressed into the summer months of 2020 and businesses were allowed to open at less than 100% capacity, which resulted in reduced traffic impacts compared to full closures.

Stay-at-home orders were correlated with a 7.8% reduction in NDT compared to when they were not in place. The implication is that SAHO may not be an effective tool in reducing vehicle traffic compared to business closure NPI policies. In the U.S., there are societal implications of asking people to stay at home. Enforcement of these policies is harder and in some states, there were no enforcement mechanisms. In contrast, in other

countries, SAHO was strictly enforced. The impact of using only vehicle trips in this study may bias the results. It will be interesting to see how people changed trips to parks and other recreational areas that are accessible by non-auto means.

Gathering bans were correlated with the lowest reduction in NDT compared to when they were not in place (1.7%) for all the NPI variables. Gathering bans limited the sizes of gatherings for most private functions with different magnitudes for different states and at different times as the pandemic progressed. For example, some states limited gatherings to 10 people, other states 25 people, and yet others to 100 people. Our model did not segregate these gathering bans into different sizes which could bias the results. Although GB resulted in the lowest NDT impacts, several large gatherings were seen as a source of virus transmission or "super-spreading" events where one person with the COVID-19 virus infects many other people, see for example [41,42]. It is thus important to take the results of this study in the context that it only evaluates how these NPI policies reduced travel rather than the spread of COVID-19. The close contacts between individuals from different households and the non-respect for COVID-19 guidelines were the culprits for GB being super spreaders.

The weekend vs. weekday variable used in this research is a proxy indicator variable that captures how traffic fluctuates based on weekday traffic and weekend traffic. The result shows that in comparison to weekends, weekdays increased NDT by 0.07%. Weekdays typically have higher traffic compared to weekend days. As expected, the variable was significant and positive.

5. Conclusions

The COVID-19 pandemic has had significant impacts on the world as a whole. In response to its spread, governments across the world imposed severe restrictions. Non-Pharmaceutical Interventions were widely implemented in the U.S. to reduce the spread of the pandemic. These NPIs resulted in a significant reduction in vehicular traffic during the pandemic. The reduction in vehicular traffic can be used to how well these policies worked in reducing travel. One of the objectives of these NPIs is to reduce interactions between people from different households during the start of a pandemic. Measuring the amount of traffic during the pandemic compared to normal times provides a proxy measure of how people altered their movements in response to NPIs. Although the overall reduction in traffic due to all these NPIs is widely known, no study, to the best of our knowledge, has attempted to disaggregate the individual effects of the different NPIs that were instituted. We developed an empirical analysis to disaggregate the total NPI policy impacts into individual effects using panel data regression models.

Several conclusions can be drawn from the results of this study. First, NPI policies worked in reducing traffic as shown by the parameter estimates. Second, NPI policies that target businesses had the highest correlation and hence were the most effective in reducing vehicular traffic in the U.S., compared to those that targeted households and individuals during the initial phases of the COVID-19 pandemic. This is intuitive as it was and continues to be easier to enforce the NPI policy variables on businesses rather than on individuals. Second, there was heterogeneity in how citizens in different states responded to similar NPI policies. In some states people respected these decisions, while in others they were not respected as much.

This study provides data about how the different NPI policy values affect travel as a proxy measure for how people responded to these policies. The results from this study can be used in epidemiology models to better forecast how novel viruses will spread, based on NPI policy measures.

We expect that the results will be different for other countries with centralized policy-making that differs from the U.S. Additionally, other countries will have different reactions to NPIs targeting individuals and businesses due to the possibilities of enforcement, and political and local beliefs. We expect the heterogeneity that was shown in our study between the states in the U.S. to exist between countries based on local beliefs and enforcement

efforts. For additional studies, a country-by-country comparison will be interesting to gauge how people in different countries responded to the NPI policy variables imposed. Adding other modes such as walking, biking, and public transit will also provide a full picture of the impact of NPI variables on travel. Extending the data collection period will permit us to further measure other effects such as pandemic fatigue, further providing decision-makers with information on how to handle pandemics as they progress.

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