Title: Vision Zero: Not a Failure but a Matter of Action

-- Policy Intervention Analysis using ARIMA Modelling

Author Name (Corresponding author) and Affiliation: Weijing Wang[a]

a: Institute of Transportation Studies (ITS), University of California (UC) Davis

Postal Address: 3009 Wickson Hall (UC Davis), 350 E Quad, Davis, CA 95616, United States.

Email Address: weijingw@ucdavis.edu

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Abstract

During 2021, the US witnessed about 43000 traffic deaths on roads, making 2021 the deadliest year in traffic safety in the past 16 years (NHTSA, 2022). With surging traffic fatalities nationwide, Vision Zero has gained its rapid growth across the country with a goal of zero traffic fatalities and serious injuries. Since Chicago's commitment to Vision Zero in 2012, to date, more than 50 cities and/or counties have adopted Vision Zero. The city of Los Angeles is one of the Vision Zero communities with the city's official announcement in 2015. Although, through Vision Zero, Los Angeles has dedicated to eliminating traffic deaths, the city experienced a more than 20 percent increase in traffic fatalities from 241 in 2020 to 294 in 2021, raising a critical question on the impact of policy interventions.

The current study asks and answers the research question: Is Vision Zero a failure or hope? In doing so, the study area is the city of Los Angeles, and the study period is from 2013 to 2021. The study uses the Autoregressive Integrated Moving Average (ARIMA) modeling to understand the policy impact and effectiveness of Vision Zero on traffic fatalities and serious injuries by different types of road users. Overall, the results suggest that Vision Zero is not a failure, in which one explanation is the outcomes of policy intervention analysis turn to be sensitive to the chosen time point when the effects of policy intervention presents. The results further show that the policy impact of Vision Zero on traffic safety differs by road users, in which pedestrians have a potential to benefit from the policy to a larger degree than others. The study concludes that working towards reducing and eventually eliminating traffic fatalities and serious injuries, further efforts on concrete methods and strategies in advancing policy implementations and equity impacts of Vison Zero are much needed.

Keywords

Vision Zero; Traffic Fatalities and Serious Injuries; Pedestrian Safety; ARIMA; Los Angeles

1. Introduction

According to a recent estimate by NHTSA (2022), the US witnessed 42915 traffic fatalities on roads during 2021, which accounts for a more than 10 percent increase from 2020, making 2021 the deadliest year in traffic safety in the past 16 years. In the last five years, California on average saw more than 3500 people who died in traffic crashes every year. And many more were seriously injured and experienced losses of loved ones and/or properties to varying degrees as a result of traffic crashes. Thus, addressing traffic crashes has become a public health imperative and is in great need of policy and funding interventions and dedications.

With surging traffic deaths nationwide, a number of traffic safety policies and initiatives across the country are announced and released in working towards eliminating traffic fatalities and serious injuries, including the Vision Zero safety policy. Vision Zero, as a traffic safety concept, was invented in Sweden in 1997 (Swedish Parliament, 1997), and firstly entered the US in 2012 (Vision Zero Network). Since its initial adoption in 2012 by the city of Chicago, the Vision Zero safety campaign has gained its rapid growth in U.S. cities. To date, more than 50 localities have committed to Vision Zero with a goal of eliminating traffic fatalities and severe injuries by a predetermined target year. Among those Vision Zero communities, about one-third are located in California. The city of Los Angeles is one of the first localities that committed to the Vision Zero policy within the state and across the country.

In August 2015, the mayor Garcetti officially announced the city's commitment to the Vision Zero safety policy, with a goal of achieving zero traffic fatalities and serious injuries by 2025. Striving toward its traffic safety goal, the city has dedicatedly implemented the policy for about seven years. However, recent news and media reports on increasing trends of traffic fatalities in Los Angeles call for an immediate action on understanding the policy intervention impact of Vision Zero. In early 2022, Los Angeles Times released a news article, titled "*Hundreds died in L.A. traffic crashes in 2021. Is Vision Zero a failure?*" (Smith, 2022), as a response of recognizing 2021 as the deadliest year of traffic fatalities in the past decade. Such questioning on the role/impact of the Vision Zero safety policy intervention is not limited to Los Angeles. Shortly after, one of the well-recognized transportation/planning news website, Planetizen, released an article asking "*Vision Zero Is Largely a Failure in the United States. Why?*" (Lonescu, 2022). Yet, little is known about the policy impact of Vision Zero among current literature, particularly in the US setting.

Motivated by those news and media reports on Vision Zero and concerned about increasing numbers of traffic fatalities, in the current study, I ask and answer the question: Whether and to what extent the policy intervention of Vision Zero helps to achieve the goal of zero traffic deaths and serious injuries? The remainder of the study is organized in the following sections: Literature Review, Study Context and Data Sources, ARIMA Models, Model Building, Results and Findings, and Conclusions.

2. Literature Review

2.1. Vision Zero and Its Impacts on Safety

Vision Zero, a traffic safety concept invented by the Swedish parliament, was firstly introduced by the Riksdag in 1997 (Swedish Parliament, 1997). The essence of Vision Zero is committing to a long-term safety goal of eliminating fatalities and serious injuries on roads (Swedish Parliament, 1997). In doing so, the Vision Zero philosophy emphasizes a shared responsibility between road users and road designers (Swedish Parliament, 1997). In the US, with increasing numbers of traffic fatalities across the country (NHTSA), Vision Zero has grown rapidly since its first adoption in Chicago in 2012 (Vision Zero Network). Since its first adoption in 2012, more than 50 localities across the country have joined the Vision Zero communities (Vision Zero Network). In 2022, the US DOT released the National Roadway Safety Strategy report in supportive of Vision Zero through a nationwide traffic safety goal of zero traffic deaths and serious injuries (US DOT, 2022), signaling further policy and funding commitments to the implementation of Vision Zero policy.

With its adoption, a number of studies have been conducted in European countries to understand the impact and effectiveness of the policy in advancing traffic safety (Johansson, 2009; Värnild, Tillgren, Larm, 2020; Värnild, Belin, Larm, Tillgren, 2019; Värnild, Belin, Tillgren, 2016). Overall, evidence drawn from prior studies suggests a relationship between the adoption of Vision Zero and a declining trend in traffic fatalities and serious injuries (Johansson, 2009; Värnild, Belin, Larm, Tillgren, 2019), suggesting a potential success of the policy intervention. However, in the U.S. setting, it is unclear whether the Vision Zero policy is effective in achieving zero traffic deaths and serious injuries.

2.2. Commitment to a Vision Zero Success

With increasing numbers of traffic fatalities across the country, the federal and state agencies have released a number of transportation safety policies and funding sources in supportive of the implementation of Vision Zero at localities. At the federal level, in February 2022, the US DOT released

Secretary of Transportation Pete Buttigieg's National Roadway Safety Strategy and officially committed to a national traffic safety goal of zero deaths and serious injuries (US DOT, 2022). Shortly afterwards, through H.B.3684-Infrastructure Investment and Jobs Act, the US DOT released the Safe Streets and Roads for All (SS4A) grant program providing 5 billion dollars over a five-year time period, to support localities in working towards zero traffic deaths and serious injuries (US DOT, 2022).

At the state level, California has joined this nationwide Vision Zero campaign and committed to zero traffic fatalities and severe injuries through senate bills, policy initiatives, and funding resources. On February 15, 2022, California DOT (Caltrans) officially announced the goal of zero traffic fatalities and serious injuries by 2050 through the Director's policy letter. California SB-932 bill (Bicycle and Pedestrian Safety), recently passed in May 2022, signals a significant step in improving traffic safety for bicyclists and pedestrians. Equally important, California AB-2336 (Vehicle: Speed Safety Pilot Program) and AB-2664 (Pedestrian Crossing Signals) provide additional policies and safety strategies in supportive of the state's goal of zero traffic fatalities and serious injuries.

At the locality level, increasing numbers of cities and/or counties across the country, including California, have committed to the Vision Zero policy in addressing traffic safety concerns within their jurisdictions (Vision Zero Network, 2022). In California, Since Vision Zero San Francisco established in 2013, nearly 15 cities and/or counties, including the city of Los Angeles, have adopted the Vision Zero safety policy, and many more localities are in the preparation process (Vision Zero Network, 2022).

In supportive of the national and statewide goal of zero traffic fatalities and serious injuries, one motivation of the current study is to provide suggestions on the implementation of relevant policy and funding interventions in addressing traffic safety and also prepare California localities for adopting and implementing the Vision Zero policy. With those statewide policy and funding commitments to zero traffic deaths, it is crucial for transportation professionals, stakeholders, and decision makers to be informed of the impact of policy intervention and the potential concrete approaches and strategies in improving the efficiency and effectiveness of policy implementation, including Vision Zero. The current project aims to make contributions from such aspects.

2.3. ARIMA for Policy Intervention Analysis

In measuring the impact of policy interventions, autoregressive integrated moving average (ARIMA) models have been extensively used in prior studies. The models present to be suitable in a wide range of research fields, for instance international trade policy (Unnikrishnan Suresh, 2016), monetary policy (Bernanke et al., 2022), public health (Griffin et al., 2021; Lopez Bernal et al., 2018, Schaffer et al., 2021), and transportation policy (Lavrenz et al., 2018; Washington et al., 2020).

In the transportation field, prior studies using ARIMA models in understanding the policy impact range from driving licensing policies (Neyens et al., 2008), the camera enforcement at intersections (Carnis Blais, 2013; Vanlaar et al., 2014), the mandatory safe belt law (Houston Richardson, 2002; Masten, 2007; Wagenaar et al., 1988), speed limit changes (Rock, 1995; Vernon et al., 2004), to pedestrian stops and/or yield policies at crosswalks and intersections (Kweon et al., 2009). Overall, prior findings suggest that ARIMA models particularly lead to informative outcomes in the time series modelling (Lavrenz et al., 2018; Washington et al., 2020), which is therefore applied in the current study for the policy intervention analysis of Vision Zero.

ARIMA models are suitable in the current study for the following reasons: 1) Compared to cross-sectional studies, time-series studies using ARIMA modelling captures underlying causal impacts and/or systematic patterns over time by eliminating noises or outliers in observations; 2) Compared to segmented regression models and difference-in-difference (DID) models (Griffin et al., 2021), ARIMA has gained its popularity in evaluating policy interventions, particularly with the presence of seasonality and autocorrelation in transportation safety studies (Lavrenz et al., 2018); 3) Policy intervention analysis using ARIMA modelling is considered as one of the best designs for establishing causal effects analysis (Cook Campbell, 2002).

3. Study Context and Data Sources

3.1. Study Context

The current study identifies the city of Los Angeles to carry out the analyses. Choosing the city of Los Angeles as the study area is suitable for the following reasons: 1) In 2021, Los Angeles witnessed a total of 294 people who were killed in traffic crashes, accounting for a more than 20 percent increase in traffic deaths from 241 in 2020 (as shown in Figure 1) and making 2021 the deadliest year in the last decade. This striking numbers and increasing trends in traffic fatalities in the city, have drawn great attention from the national and local news on the role/impact of Vison Zero Los Angeles. 2) To date, more than 50 localities have joined the Vision Zero communities across the country, and fourteen of them (about one-third) are located in California. And Los Angeles is one of the localities that have implemented the Vision Zero policy for the longest time, making the city a desirable place to understand the impact and effectiveness of the policy. 3) The study results drawn from Los Angeles will provide concrete suggestions and recommendations to the Vision Zero community peers across the country and the state in advancing the efficacy and effectiveness of the policy implementation practices.

4) At the state level, California has made dedicated policy and funding efforts in supportive of localities in achieving the goal of zero traffic deaths through increasing numbers of senate and assembly bills. Some examples of policy commitments, which promisingly will lead to funding commitments, include Caltrans' policy commits to zero deaths and serious injuries by 2050 (Caltrans, 2022), a recently passed bill of SB-932 (Bicycle and Pedestrian Safety), AB 2336 (Vehicle: Speed Safety Pilot Program), and AB-2664 (Pedestrian Crossing Signals). Moving forward, the results in the current study through providing some evidence on the policy impact and effects of Vision Zero will be beneficial to transportation safety practices in many aspects. Specifically, the study results will 1) pave the way for California localities in advancing the effectiveness the Vision Zero policy, 2) promote the implementation and effectiveness of the current and in-process statewide traffic safety policies and/initiatives, 3) help

decision-makers and stakeholders in further identifying the targeted policies and funding opportunities in supporting the statewide road safety goal of zero traffic fatalities and serious injuries by 2050 in California.

3.2. Data Sources

In carrying out the current study, several publicly-accessible data sources are used to construct the analysis-ready dataset. 1) The websites of Vision Zero Network[1] and Vision Zero Los Angeles[2] provide a context in understanding the adoption and implementation of the Vision Zero safety policy at the national, state (i.e., California), and locality levels. 2) The traffic crash data in the city of Los Angeles[3] is retrieved from the Los Angeles Open Data[4], providing crash records from 2010 to present. 3) The American Community Survey (ACS) 5-Year from US Census is used to indicate and/or measure sociodemographic and economic characteristics of the study context.

Overall, the raw data of traffic crashes returns a total of 569,434 collision records that occurred between 2010 and 2021. The raw data includes various features of each crash record, for instance, date and time, injury severity, and location, and types of road users. The raw crash data also provides the indicators of sociodemographic characteristics of crash victims, including age, gender, and race and ethnicity. In understanding the policy impact of Vision Zero, given its essential goal of reducing and eventually eliminating traffic fatalities and/or serious injuries, one preliminary step is to identify those crashes that led to fatalities and/or serious injuries. To do so, I particularly focus on three types of traffic crashes: 1) traffic fatalities, 2) traffic fatalities and serious injuries, 3) pedestrian traffic fatalities and serious injuries, in constructing the analysis-ready data.

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[1] Vision Zero Network: https://visionzeronetwork.org/
[2] Vision Zero Los Angeles: http://vision-zero.ua5.land/
[3] Traffic Collison Data: https://data.lacity.org/Public-Safety/Traffic-Collision-Data-from-2010-to-Present/d5tf-ez2w
[4] Los Angeles Open Data: https://data.lacity.org/

Identifying and categorizing traffic crashes of interest rely on the "MO Codes" in the raw data. The "MO" stands for "Modus Operandi", which is defined as "*activities associated with the suspect in commission of the crime*" by Los Angeles Police Department (LAPD). Specifically, the following steps are taken to prepare the analysis-ready dataset. 1) I identify and select those crash records with the MO code of 3027 indicating fatal injury, and with the MO code of 3024 indicating severe injury (see Table 1 for details). 2) I select the fatal crash records that occurred between January 1, 2013, and December 31, 2021. Choosing this study period is because the number of fatal crashes before 2013 presents to be significantly smaller than that in 2013 and after (the yearly traffic fatalities is 59 in 2011 and 162 in 2012), signaling data errors as a comparison with the city crash reports (City of Los Angeles, Inter-Department Memorandum, 2021[5]). Thus, it is appropriate to use the study period from January 2013 to December 2021, in which the policy intervention occurred in August 2015. 3) I further apply the MO code of 3003 to identify those traffic crashes in which pedestrians were involved in (see Table 1), for the purpose of pedestrian safety analyses below.

[Table 1. Selected Features from the Raw Data]

Figure 1-3 show the traffic fatality trend in Los Angeles from 2013 to 2021. Specifically, the overall traffic fatalities increased by nearly 50 percent from 198 in 2013 to 293 in 2021, making 2021 the deadliest year across the study period (see Figure 1). Among traffic fatalities, nearly 50 percent of traffic deaths were pedestrians, and this number of pedestrian deaths increased from 91 in 2013 to 132 in 2021, raising significant concerns on traffic safety particularly for vulnerable road users (see Figure 1 and Figure 3). Similar patterns present in both traffic fatalities and serious injuries (see Figure 2). Yet, many more were serious injured in traffic crashes regardless of travel modes (see Figure 2).

[Figure 1. Traffic Fatality Trend in Los Angeles, 2013 – 2021]

[Figure 2. Traffic Fatality and Serious Injury Trend in Los Angeles, 2013 – 2021]

[5] City of Los Angeles, 2021: https://clkrep.lacity.org/onlinedocs/2017/17-1137_rpt_dot_3-30-21.pdf#page=9

[Figure 3. Percentage of Pedestrian Involved Crashes by Injury Severity]

4. ARIMA Models

4.1. Assumptions

Applying ARIMA models in policy intervention analysis requires meeting several modelling assumptions: 1) seasonality, 2) stationarity, and 3) autocorrelation. Starting with the seasonality, data with the seasonality presents a fixed/known pattern or trend, occurring at a regular time interval, and requires an application of seasonal ARIMA models. In traffic crash studies, the yearly, seasonal, and/or monthly trends have been frequently used in capturing variations in influential factors of the occurrence of traffic fatalities and/or serious injuries such as weather conditions during the year. Implementing ARIMA models also makes a standard assumption that the ready data is stationary. Data meeting the stationarity assumption 1) shows a constant mean, and 2) has a constant variance in which the standard deviation and variance of the residuals are constant. 3) The stationarity also requires constant covariance of a data set is solely the function of a time interval between outcome measures. Meeting the stationarity assumption can often be achieved through differencing data itself, which is used in the current study.

ARIMA models is by nature a class of modelling in analyzing and/or forecasting time-series observations. One challenge of time-series analysis is data observations are often autocorrelated. Autocorrelation indicates that one observation is a function of its value(s) that is/are measured at previous time points, which presents to be a violation of the independence assumption of regression analysis. To detect the autocorrelation, the autocorrelation functions (ACFs) and the partial autocorrelation functions (PACFs) are frequently used in the literature and present to be effective. I will provide further clarifications on the ACFs and PACFs in the analyses below. When the autocorrelation issue presents, taking the first-differencing is often suitable to conduct data transformation, which is also used in the current study.

4.2. Specifications

ARIMA modelling predicts the outcome measures solely as a function of one or multiple values at previous time points and error terms. ARIMA, the acronym of the autoregressive integrated moving average, is essentially a combination of autoregressive (AR) models, moving average (MA) models, and integrated also known as differencing (Fattah et al., 2018.)). Thus, the specifications of ARIMA are present in three components, respectively.

The AR models component is defined as:

$$Y_t = c + \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \dots + \Phi_p Y_{t-p} + \epsilon_t$$

Where Y_t is the outcome measure. c is a constant. ϕ denotes the autocorrelation between one time-series observation and its one or multiple measures at previous time points. p indicates the number of time lags, and ϵ denotes error terms.

And the MA models component is defined as:

$$Y_t = c + \theta_1 \epsilon_{t-1} + \theta_2 \epsilon_{t-2} + \dots + \theta_q \epsilon_{q-1}$$

Where Y_t is the outcome measure. θ denotes the autocorrelation of error terms, and q indicates the number of time lags.

Lastly, the integrated/differencing component is defined as:

$$Y'_t = Y_t + Y_{t-1}$$

In which the differencing function is used to address the non-stationarity issue and transform data itself to meet the stationarity assumption required in implementing ARIMA models.

5. Model Building

In preparing for model building, Figure 4 shows the monthly time-series data for traffic crashes of interest, including traffic fatality, traffic fatality and serious injury, and pedestrian traffic fatality and serious injury, respectively. The study period used here is between January 2013 and December 2021. In Figure 4, the light blue dotted line indicates the time when the Vision Zero policy was officially adopted in the city of Los Angeles, that is August 2015. Turning to those modelling assumptions stated above and carrying out the analyses, Figure 5 shows the workflow and steps that are taken to construct and select the appropriate models.

[Figure 4. Monthly Time Series Data for Traffic Crashes in Los Angeles, January 2013 – December 2021]

[Figure 5. Workflow for Model Building and Performance Measures]

For the simplicity, in the current section, the process and steps of model building and fitting are demonstrated in detail only for traffic fatalities. The same process and steps are carried out for traffic fatalities and serious injuries, and pedestrian fatalities and serious injuries, and relevant results are reported in the Results and Findings below.

5.1. Identify and Select Structural Breaks

The model building process starts with identifying and selecting the breakpoints (Step 1). Although one primary goal of the current study is to understand the policy impact of the Vision Zero on addressing traffic crashes, it is unknown, at least ambiguous, that when the policy impact presents in practices if there is any. Thus, one primary step is to identify the breakpoints in the dataset (Bai & Perron, 2003) that could serve as the date(s) when the policy started/starts show its effects in reducing traffic fatalities and serious injuries. Doing so relies on the breakpoints() function in R, which computes the structural breaks in regression analysis and split data observations into several segments (Bai & Perron, 2003). In the current study, the breakpoints() function returns the structural breaks that can be potentially used as the time points in predicting traffic crashes in a counterfactual scenario.

Table 2 is the results of the breakpoints() function for traffic fatalities. Specifically, the results show five alternatives of the structural breaks (from m = 1 to m = 5), in comparison with the data itself without any breaks (m = 0). The values of RSS[6] and BIC[7] are used to select the structural break(s) to calculate relevant more accurate counterfactual predictions, in which the structural break(s) with smaller value(s) of RSS and BIC is/are more desirable. In identifying the appropriate structural breaks, the following two criteria are considered: 1) Any structural breaks shown in 2015 or before are not included, because it is intuitively implausible to expect policy impacts before or any time soon after the policy was adopted (August 2015); 2) the selected structural break has relatively small values of RSS and BIC. As a result, the structural break in which m is equal to 4, turns to be a more suitable option (see Table 2). Figure 6 is a visualization of the selected structural break (m = 4), suggesting there are four time points presenting as the potential start of policy impacts.

[Table 2. Structural Break Candidates of Presenting Policy Impacts – Traffic Fatality]

[Figure 6. Structural Breakpoints and the Selected Break (m = 4) - Traffic Fatality]

5.2. Detect Seasonality and Stationarity

I then move to detecting whether the data presents be seasonal and/or stationary. In doing so, I start with the decomposition of time-series data (see Figure 7). Figure 7 presents the results of using the decompose() function in R, showing four components of the time series data: the observed data, trend, seasonality, and randomness. Specifically, the plot of seasonality suggests that the data itself presents be seasonal with a yearly time interval, and the plot of observed data shows that the data itself is non-stationary. In addition, the ACFs and PACFs are used to reveal further evidence on the results (see Figure 8), which turn to be consistent with the results of decomposing time-series data (see Figure 7).

[6] RSS stands for Residual Sum of Squares.
[7] BIC stands for Bayesian Information Criterion.

Specifically, in Figure 8, the ACF plot shows the correlation between one observation with its one or multiple values at previous time points by various lags, in which the lag is defined as the number of time points. And the PACF plot shows the correlation between one observation with its one or multiple values at previous time points that cannot be explained by the correlation at a lower order lag. Overall the results in Figure 8 show that many ACF values are above the autocorrelation boundaries, and the majority of ACFs are clustered on one side of the zero-benchmark line (above the line in this case). The PACF plot shows a similar pattern. Thus, it is reasonable to conclude that the current data is non-stationary, and further data transformation is needed.

[Figure 7. Decomposition of Time Series Data - Traffic Fatality]

[Figure 8. Plots of ACF and PACF for Data Itself - Traffic Fatality]

5.3. Transform Data through Differencing

To address the non-stationarity issue detected above, I transform the data by taking the first-order differencing. The results of ACF and PACF are shown in Figure 9, suggesting significant improvements. With data transformation, the differenced data presents a constant variance. And the majority values of ACF and PACF are within the autocorrelation boundaries of the blue line and spread out on both sides of the zero-benchmark line, suggesting the differenced data is stationary.

[Figure 9. Plots of ACF and PACF for Differenced Data - Traffic Fatality]

5.4. Identify Parameters and Model(s)

To calculate an accurate prediction, one critical step is to identify appropriate parameters and models. Doing so requires solving the following SARIMA equation. SARIMA stands for the seasonal ARIMA, which is suitable here to capture the seasonality in the data as detected above.

$$\text{SARIMA} \ (p, d, q)\ (P, D, Q)_m$$

Specifically, SARIMA has two portions of the parameters: the non-seasonal portion and the seasonal portion. The lowercase portion *(p, d, q)* are parameters for the non-seasonable portion, and the uppercase portion (P, D, Q) are parameters for the seasonal portion. m indicates the number of observations per season. With the yearly trend shown in Figure 7 (i.e., the plot of seasonality), I choose the number 12 for the m, indicating 12 months in a year, for the following analyses.

To preselect the potential models, two approaches are applied. First, I use the auto.arima() function, developed by Hyndman and Khandakar (2008), to return the chosen best model. Specifically, the Hyndman and Khandakar algorithm takes iterations to minimize the AIC value and identifies the one with the smallest AIC as the best model. As a result, the the auto.arima() function returns the chose best model ARIMA(0, 1, 1) (see Table 3).

I then use the ACF and PACF plots for differenced data (see Figure 9) to identify alternative parameters and construct alternative model candidates with a combination of the selected parameters. Specifically, in Figure 9, the ACF and PACF plots both show the spikes at the lag 3 and the lag 12. Those spikes present in the plots suggest that for the non-seasonal portion, the potential values of p and q are 3, and for the seasonal portion, the potential values of P and Q are 1. Also I choose 1 as the value for D because the data differencing is taken to meet the stationarity assumption. As no additional data differencing is taken, d is equal to zero here. Thus, one alternative model is defined as ARIMA(3, 0, 3)(1, 1, 1)[12] (see Table 3). For a comparison, Table 3 also lists the performance measures of AIC, AICc, and BIC for model candidates, in which the model with smaller values of the measures indicates a higher prediction performance in a counterfactual scenario below. Thus, those measures and metrics in Table 3 suggest that ARIMA(3, 0, 3)(1, 1, 1)[12] is a more appropriate model candidate.

[Table 3. Model Candidates and Performance Measures – Traffic Fatality]

5.5. Perform Diagnostic Measures

With those identified model candidates, in this step, I further preform diagnostic measures to select the final model for the post-policy intervention prediction. The results of diagnostic measures are shown in Figure 10 for ARIMA(0, 1, 1) and in Figure 11 for ARIMA(3, 0, 3) (1, 1, 1) [12], respectively. Comparing the results between two figures, 1) the ACF of residuals present white noise (Moffat & Akpan, 2019) in Figure 12, in which all values are within the autocorrelation boundaries; 2) the p-values for Ljung-Box present to be significant in Figure 12; 3) the Normal Q-Q plot in Figure 12 suggests that the data meets the normality assumption relatively well. Thus, it is reasonable to select the model of ARIMA(3, 0, 3) (1, 1, 1) [12] as the final model to conduct counterfactual predictions below.

[Figure 10. Diagnostic Measures for ARIMA(0, 1, 1)]

[Figure 11. Diagnostic Measures for ARIMA(3, 0, 3) (1, 1, 1) [12]]

6. Results and Findings

6.1. Calculate Counterfactual Predictions

With the selected model of ARIMA(3, 0, 3) (1, 1, 1) [12], I now turn to predicting traffic fatalities in a counterfactual scenario without the Vision Zero policy. In doing so, I use the structural breaks identified in the model building section (see Table 2 and Figure 6) as the potential dates to calculate predictions. In Figure 12 below, I apply the dates of April 2018, March 2019, and July 2020 in counterfactual predictions for a comparison.

The results in Figure 12 show a comparison between the counterfactual predictions without the Vision Zero policy and the observed data with the adopted policy. Specifically, the y-axis indicates the number of monthly traffic fatality; the x-axis is the time indicated by each month from January 2013 to December 2021; the vertical dotted line in light blue indicates the time when the Vison Zero policy was officially adopted; the vertical dotted line in grey indicates the time when the policy started showing its impact on the occurrence of traffic fatalities; the black line shows the traffic fatality records collected by the Los Angeles police department; and the red line indicates the predicted values of traffic fatalities in a scenario without the Vision Zero policy intervention.

To answer my research question, Vision Zero is a failure or hope, overall, the study results on traffic fatalities suggest that with the policy intervention, the occurrence of traffic fatalities in Los Angeles does not present significant changes, in comparison with that in a counterfactual scenario without the policy. However, as shown in Figure 12, the results of counterfactual predictions, interpreted as the impact of Vision Zero, vary by the dates when the policy intervention analysis occurs. This suggests that the timing of policy intervention analysis matters.

[Figure 12. Counterfactual Prediction vs. Observed Data – Traffic Fatality]

6.2. Policy Impact on Fatality and Serious Injury

I then turn to the policy impact of Vision Zero on traffic fatalities and serious injuries. Starting with the structural breaks in the data including both traffic fatalities and serious injuries, the results suggest that the structural breaks in August 2017, December 2018, and/or August 2020, turn to be appropriate candidates for conducting counterfactual predictions. As shown in Table 4, for the selected structural breaks (m = 4), the values of RSS and BIC are relevant small as a comparison with other candidates, suggesting the model is suitable and valid. Following the same process of model building demonstrated/illustrated above, the results present that ARIMA(1, 0, 2)(0, 1, 1)[12] is the appropriate chosen model. The performance measures of the selected model are shown in Table 5, and the diagnostic measures are shown in Figure 13. The results collectively show the model of ARIMA(1, 0, 2)(0, 1, 1)[12] is a valid option for the counterfactual predictions.

[Table 4. Structural Breaks of Presenting Policy Impacts – Traffic Fatality and Serious Injury]

[Table 5. Model Candidates and Performance Measures – Traffic Fatality and Serious Injury]

[Figure 13. Diagnostic Measures for ARIMA(1, 0, 2) (0, 1, 1) [12]]

Figure 14 shows a comparison of the counterfactual predictions (in red) and the observed data (in black). Overall, the results are more distinctive in presenting the significance of the timing in conducting policy intervention analysis. Specifically, the first plot with August 2017 and the third plot with August 2020 as the break dates respectively, suggest that the policy does not show significant impacts on the occurrence of traffic fatalities and serious injuries. However, the second plot with December 2018 as the break date shows that the policy does show beneficial effects on reducing the number of traffic fatalities and serious injuries. Still, it is noteworthy that the dramatic drop in the observed data (in black) around March 2020 is likely a result of the stay-at-home policy due to COVID-19 (March 19, 2020, COVID-19 Orders, Office of Los Angeles), at least partially.

[Figure 14. Counterfactual Prediction vs. Observed Data – Traffic Fatality and Serious Injury]

6.3. Policy Impact on Pedestrian Safety

Similarly, to understand the policy impact of Vision Zero on pedestrian safety, I use the number of pedestrian fatalities and serious injuries as the outcome measures. Starting with the structural breaks, the results suggest that the structural breaks in June 2017 and January 2020, turn to be appropriate candidates for conducting counterfactual predictions (see Table 6), and I also include the break date in July 2016 for a comparison purpose. The process of modelling building and fitting returns that ARIMA(1, 0, 1)(0, 1, 1)[12] is the appropriate chosen model. The performance measures of the selected model are shown in Table 7, and the diagnostic measures are shown in Figure 15. The results collectively show the model of ARIMA(1, 0, 1)(0, 1, 1)[12] is a valid option for the counterfactual predictions.

[Table 6. Structural Breaks of Presenting Policy Impacts – Pedestrian Fatality/Serious Injury]

[Table 7. Model Candidates and Performance Measures – Pedestrian Fatality/Serious Injury]

[Figure 15. Diagnostic Measures for ARIMA(1, 0, 1) (0, 1, 1) [12]]

Consistent with the earlier findings, the results in Figure 15 further emphasize the significance of the timing in conducting policy intervention analysis. The first two plots with July 2016 and June 2017 as the break dates respectively, suggest that the policy does not show significant impacts on pedestrian fatalities and serious injuries. Yet, the third plot with January 2020 as the break date shows that the number of pedestrian fatalities and serious injuries dropped with the adoption of Vision Zero policy. Still, COVID-19, that started at the beginning of 2020, could be an influential factor in interpreting the results in Figure 16.

[Figure 16. Counterfactual Prediction vs. Observed Data – Pedestrian Fatality and Serious Injury]

7. Conclusions

7.1. Implications

The current study contributes to both the academic field and the transportation safety practices in many aspects. As one may recall, the Vision Zero policy was first adopted in Chicago in 2012. Since then, the Vision Zero communities have grown rapidly, and many large cities including New York, San Francisco, and Los Angeles joined the communities in the last decade. To date, more than 50 localities across the country have committed to Vision Zero, and many more localities are in the preparation process. With increasing popularities of the Vision Zero policy, it becomes important and even imperative to understand the impact and effectiveness of the policy intervention in addressing traffic fatalities and serious injuries. However, relevant research on the topic, particularly in the US setting, remains very limited if any at all.

Thus, the current study contributes to existing literature on Vision Zero with a purpose of raising the awareness of measuring the policy implementation and evaluating the policy impacts through concrete methods, approaches, and strategies. Specifically, as a response to the media reports on whether Vision Zero fails in the US, the study results suggest that the timing of conducting the policy intervention analysis is crucial in determining whether the Vision Zero policy is effective or otherwise. At its minimum, at the current phase of Vision Zero, it is inconsiderate rushing into a conclusion that Vision Zero is a failure. Because whether and to what extent the Vision Zero policy is effective in reducing traffic fatalities is sensitive to the chosen break dates when the impact of policy interventions presents, as shown in the results above.

In addition, relevant evidence on the impact and effectiveness of Vision Zero are only present recently, with those studies conducted in Sweden and/or other EU countries (Wegman et al., 2015; Värnild et al., 2020), after the policy was first introduced in 1997. In other words, if the US sees the Vision Zero policy in Sweden as a safety initiative model, a comparative policy intervention analysis in the US is expected to occur five to ten years from now. Compared to prior studies in Sweden and/or other EU countries, Los Angeles adopted the Vision Zero policy in 2015, accounting for a much shorter time period. Thus, taking those factors into consideration, in order to achieving the goal of zero traffic fatalities and serious injuries in the US, perhaps, it is more important to advance the effectiveness of policy implementation and measure the policy impact instead of claiming the policy as a failure. Too soon for such a strong conclusion on a policy aiming to save many lives in traffic crashes.

Turning to transportation safety practices, the timing of investing in safe streets for all and addressing traffic safety concerns cannot be any better. At the federal level, the fundamental philosophies and concepts of Vision Zero have been adopted and promoted (US DOT, 2022), with an intention of supporting Vison Zero as a nationwide traffic safety campaign. At the state level, many states, including California, have recognized the urgency of addressing traffic fatalities and serious injuries and publicly committed to the Vision Zero initiatives, for instance, Caltrans' commitment to eliminating traffic fatalities and serious injuries by 2050 (Caltrans, 2022) and a recently passed bill of SB-932 (Bicycle and Pedestrian Safety).

Moving forward, to achieve the goal of zero traffic deaths and serious injuries by 2050 and promote the policy implementations, it is crucial for transportation professionals, stakeholders, and elected officials to understand the impact of the Vision Zero safety policy intervention in advancing traffic safety. In doing so, the results in the current study make contributions through 1) promoting a concrete method/tool to those Vision Zero communities in monitoring the implementation of their Vision Zero programs and allocating their resources in a more effective and efficient way within their jurisdictions, 2) preparing those localities who are interested the Vison Zero policy for being part of the efforts of eliminating traffic fatalities and advancing safe streets across the country, 3) providing additional insights to decision-makers at the national, state, and local levels, such as California, in further providing the targeted policy and funding support to those localities in promoting and advancing policy implementations, such as SB-932, and meet the goal of zero traffic deaths.

7.2. Discussions

The current study also builds on certain assumptions born by the methods used and the context of the study area. I now turn to discussing the assumptions and limitations of the current study. First, admittedly, the application of ARIMA modelling in the policy intervention analysis builds on certain assumptions. For instance, the ARIMA model, as part of the causality analysis community, only considers the outcome measures themselves (i.e., the number of traffic fatalities in this case) and does not take other contributing factors into account. However, it is important to recognize that alternative methods to ARIMA, such as difference-in-difference (DID) models in conducting policy impact analyses (Barajas, 2021), are neither feasible nor robust in carrying out the current study. Because DID models require a comparison between treatment groups and control groups as a function of the policy intervention. However, at the current phase of Vision Zero, the size of the control groups (i.e., those localities not adopting Vision Zero) is much larger than that of treatment groups (i.e., those Vision Zero communities). Consequently, applying DID models will lead to a highly imbalanced dataset and further result in additional limitations and constraints in the methods and/or analyses. Thus, I argue that under its own assumptions, ARIMA modelling, at its minimum, serves as a practical tool to localities and researchers to draw a preliminary picture on whether and to what extent Vision Zero can be implemented effectively and efficiently in addressing traffic safety.

Second, the study area in the current project is the city of Los Angeles. It is unlikely that the study results will present to be the same in other Vision Zero communities. However, the ARIMA modelling presents to be an easily replicable method, which makes the reproducibility of the current study in other communities feasible. With the crash records reported by the police department, practitioners can apply the same methodology to obtain a preliminary understanding on the impact of

Vision Zero within their jurisdictions and when the impact presents if any. In addition, the current study does not intend to draw a final conclusion on whether Vision Zero is a failure or not. Instead, the study aims to provide a tool to the Vision Zero communities and those who are interested in becoming one, to measure the policy implementation and allocate ever-limited resources in a more effective and efficient way. Even in the circumstances that Vision Zero does not present a significant impact on traffic crashes yet, what is more promising to pursue is to take the concrete and targeted approaches, strategies, and countermeasures to improve and advance the efficacy and effectiveness of policy implementation and achieve the goal of mitigating and eventually eliminating traffic fatalities and/or serious injuries in a foreseeable time horizon.

Declaration of Interest

None.

Acknowledgements

The author would like to thank Jesus M Barajas (Professor, University of California Davis) for his valuable comments and the anonymous reviewers for their reading of the current manuscript.

Funding Sources

The current study received no specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

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