Highlights

Bayesian vector autoregressive analysis of macroeconomic and transport influences on urban traffic accidents

Jieling Jin

- Bayesian vector autoregressive model is introduced to solve the problem of time series analysis in the case of small samples for traffic accident analysis.
- Identified that urban economic growth contributes to the reduction of traffic accidents in the long term, while population growth has a positive effect on traffic accidents in the short term.
- Revealed that road average speed and private vehicle ownership is considered to increase traffic accidents in long duration, and the positive effect is greatest for road average speed.
- Uncovered that bus ownership and subway rail mileage have a long-term negative effect, and the negative effect is greatest for subway rail mileage.
Bayesian vector autoregressive analysis of macroeconomic and transport influences on urban traffic accidents

Jieling Jin

Urban Transport Research Center, School of Traffic and Transportation Engineering, Central South University, Changsha, Hunan, China

ARTICLE INFO

Keywords:
urban traffic accidents
macroeconomic factors
macro-transport factors
vector autoregressive model
Bayesian inference

ABSTRACT

The macro influencing factors analysis of urban traffic safety is important to guide the direction of urban development to reduce the frequency of traffic accidents. In this study, a Bayesian vector autoregressive (BVAR) model was developed to explore the impact of six macro-level economic and transport factors, including population, GDP, private vehicle ownership, bus ownership, subway rail mileage and road average speed on traffic accidents with the small sample size transport annual report data in Beijing. The results show that the BVAR model was suitable for time series analysis of traffic accidents in small sample situations. In macroeconomic factors, GDP growth was considered to reduce the number of traffic accidents in the long term, while population growth had a positive effect on traffic accidents in the short term. With respect to macro-transport factors, road average speed and private vehicle ownership was perceived to increase traffic accidents in long duration, whereas bus ownership and subway rail mileage had long-term negative effects, with the greatest positive effect for road average speed and the greatest negative effect for subway rail mileage. This study suggests that government departments can reduce the number of traffic accidents by increasing investment in public transportation infrastructures, limiting private vehicles and road speed.

1. Introduction

According to the World Health Organization (2021) statistics, approximately 1.3 million people die each year as a result of road traffic crashes, between 20 and 50 million more people suffer non-fatal injuries, with many incurring a disability as a result of their injury, and road traffic crashes cost most countries 3% of their gross domestic product. Traffic safety has become one of the focus issues in the field of transportation, due to the serious hazards of road traffic accidents. Exploring the influencing factors of traffic accidents has attracted the attention of many researchers. Many researchers have found that four categories of micro factors in the elements of the transport system, including human (Zhang et al., 2019), vehicle (Almeida et al., 2013), road (Wu et al., 2020) and environment (Lankaraniet al., 2014) significantly impact traffic accidents. And with recent advances in computer technologies and sensing technologies for micro factors, scholars have made some achievements in analysing the micro influences on traffic accidents which have already contributed to the development of intelligent transportation technologies such as vehicle-road collaboration (Qu et al., 2019) and driverlessness (Gang, 2019).

Researchers have also begun to discuss how urban macro-level factors can impact road traffic accidents. The economic developments have been shown to have some positive (Lee et al., 2008) or negative (Apparao et al., 2013) impact on the number of traffic accidents (Sirajudeen et al., 2021), and other macroeconomic factors also be identified some relationship between them and traffic accidents, such as there is a positive contribution of population growth to the number of road accidents (Li et al., 2018). Moreover, the number of traffic accidents is affected by macro-transport factors such as private vehicle ownership (Sun et al., 2019) and road average speed (Wang et al., 2009) have a positive contribution to traffic accidents, while public transport infrastructure has a negative impact (Soehodho, 2017). However, the studies that simultaneously analyze the temporal dynamic relationship between traffic accidents and macroeconomic and transport factors continue to be lacking.

Most of the existing studies on the analysis of traffic accident influencing factors have focused on statistical methods. The linear regression (Iwata et al., 2010), logistic regression (Liu et al., 2020), structural equation models (Najaf et al., 2018) and other statistical models (Ghasedi et al., 2021) are used to explain the the correlation between accidents and road alignment characteristics, economic growth and other influences. In addition, while these traditional statistical
Bayesian vector autoregressive analysis

analysis methods can analyze the influencing factors of accidents, they are difficult to reveal the dynamic relationship
among the factors and accidents, since they do not consider temporal characteristics.

Some time-series analysis methods have also been explored to analyze traffic accident influences in previous studies.
For instance, a combination of autoregressive distributed lag and vector error correction model is used to determine the
short or long term causal relationships between the number of road accidents and socio-economic development Li et al.
(2018), a vector autoregressive model is developed to explore the dynamic relationship between motorway collisions
and road infrastructure, social demographics, traffic and weather characteristics Michalaki et al. (2016). These time
series models can find the temporal characteristics of accident influencing factors, but the traffic accident multivariate
time series analysis in the case of small samples is still a difficult task.

The urban traffic accidents time-series data which containing macro-level economic and transport variables are
mostly collected by annual city statistics report, and with multivariate and small sample characteristics. We proposed
to use a Bayesian vector autoregressive (BVAR) model for analyzing the impact of the macroeconomic and transport
factors on traffic accidents based on the annual city statistics time series data. The BVAR model has been widely used
by researchers in the field of macroeconomic (Ma et al., 2021; Giannone et al., 2014; DeJong et al., 2000) due to its
advantages of being able to deal with time-series data and achieving good parameter estimation results with small
samples, and the BVAR study in the field of traffic safety is beginning to appear Li et al., 2019.

This paper mainly solves the following two problems: (1) Determining the Bayesian vector autoregressive model
can be used to obtain explore the small sample size time series data structure in the traffic accident analysis field; (2)
Exploring the dynamic influence of the macro-level economic and transport factors on traffic accidents.

The rest of the paper is organized as follows: The data sources and preparation are given in section 2. Section 3 de-
scribes the methodology adopted. Section 4 introduces the detailed results and discussion. Section 5 gives conclusions
and directions for future work.

2. Data preparation

2.1. Data collection

In this study, the dataset was collected from the Beijing Transport Development Annual Report from 2003 to 2020
published by the Beijing Transport Institute. This study covers all 13 administrative regions of Beijing. According
to relevant studies and data characteristics of the annual reports, seven time series variables including the number
of annual traffic accidents were selected for analysis. Other variables in the dataset could be divided into two types:
macroeconomic and transport factors, macroeconomic variables included urban GDP and population, while macro-
transport variables included urban subway rail mileage, bus ownership, private vehicle ownership and road average
speed.

Figure 1 reveals the evolutions of these time series. As can be seen in Figure 1, the number of traffic accidents in
Beijing had declined significantly over time, from over 12,000 in 2003 to around 3,000 in 2020. Population and GDP
were both on a growth trend, the population growth slowed around 2015, while GDP has been growing at a steady
rate. Private vehicle and bus ownership both tended to increase over time amidst fluctuations. Subway rail mileage
had been growing at a relatively steady rate, while the road average speed in 2020 was significantly lower compared
to 2003.

2.2. Data normalisation

Table 1 presents the descriptive statistical information of the dataset, as shown in the table, the dataset contained
18 yearly times series data, and the magnitudes of the variables were different from each other. To address the impact
of different data magnitudes on the analysis results, we normalized all variables within the dataset to between 0 and 1
before being substituted into the model. Assume that the variable takes the value $X$ and the normalized variable takes
the value $\tilde{X}$ as follows:

$$
\tilde{X} = \frac{X - X_{\min}}{X_{\max} - X_{\min}} \tag{1}
$$

3. Methodology

This paper developed a Bayesian vector autoregressive (BVAR) model to analyse urban macro factors of traffic
accidents. The BVAR model is a special form of vector autoregressive (VAR) model. To understand the BVAR model,
Bayesian vector autoregressive analysis

Figure 1: Variables time-series distribution
Table 1
Summary of variables and descriptive statistics.

| Variables                          | Times Series | Observations | Mean   | Median  | Min    | Max    | SD     |
|-----------------------------------|--------------|--------------|--------|---------|--------|--------|--------|
| Accidents()                       | Yearly       | 18           | 5101.44| 4181.00 | 2639.00| 12053.00| 2743.98|
| Population(ten thousand)          | Yearly       | 18           | 1872.88| 1989.90 | 1423.00| 2172.90| 292.01 |
| GDP(billion yuan)                 | Yearly       | 18           | 1618.19| 1518.28 | 321.27 | 3537.13| 994.11 |
| Private Vehicle Ownership         | Yearly       | 18           | 343.83 | 396.85  | 119.50 | 513.00 | 130.88 |
| Bus Ownership(ten thousand)       | Yearly       | 18           | 2.14   | 2.16    | 1.68   | 2.76   | 0.29   |
| Subway Rail Mileage(km)           | Yearly       | 18           | 349.17 | 354.00  | 75.00  | 669.00 | 213.55 |
| Road Average Speed(km/h)          | Yearly       | 18           | 30.40  | 29.85   | 25.85  | 36.30  | 2.70   |

one can start with the VAR model.

3.1. Vector Autoregressive model

VAR models are multivariate time series analysis models which are used extensively for macroeconomic analysis since their introduction by Sims (1980). They can capture the stochastic trends which separate the long-run relations from the short-run dynamics of the generation process of a set of variables and describe the dynamic structure and the joint generation mechanism of the variables involved (Lütkepohl, 2013). Consequently, VAR models can be applied to factor analysis of multivariate time series data. The $N \times 1$ vector $Y = \{y_{1T}, y_{2T}, \ldots, y_{NT}\} \in \mathbb{R}^{N \times T}$ is a multivariate time series data. The number of observations is $N$ and the number of time series is $T$. In the matrix $Y$, at any $t$-th time interval, the observed value is:

$$y_t = (y_{1t}, y_{2t}, \ldots, y_{Nt}) \in \mathbb{R}^N,$$

(2)

Given multivariate time series data as $Y \in \mathbb{R}^{N \times T}$, the following linear expression for the vector autoregressive model exists for any $t$-th time interval:

$$y_t = c + \sum_{k=1}^{d} A_k y_{t-k} + \epsilon_t, t = d + 1, \ldots, T,$$

(3)

where $c = (c_1, \ldots, c_N)^T$ is an $N \times 1$ vector of constants. $A_k \in \mathbb{R}^{N \times N}$, $k = 1, 2, \ldots, d$ are the coefficient matrices of the vector autoregressive model. $\epsilon_t$ is a Gaussian noise vector satisfying $\epsilon_t \sim \mathcal{N}(0, \Sigma)$. $\Sigma$ is an $N \times N$ positive definite matrix. The traditional VAR model usually use the maximum likelihood method to estimate the parameters (Ni and Sun, 2005).

3.2. Bayesian Vector Autoregressive model

As we all know, the sample size plays an important role in the estimation of the parameters of this model because when the dimensionality of the time series sample is small, the estimates are not precise with the traditional method such as maximum likelihood and least squares method (Michail and Melas, 2020). In the case of a multivariate model there are usually a large number of parameters that would need to be estimated, it is difficult to obtain precise estimates for all the parameters applicable to a data set with a limited number of observations, without prior information or some form of parameter shrinkage. While traditional VAR models have a problem with the loss of degrees Bayesian techniques can be used to provide parameter estimates where the models include many variables and relatively little data.

In this paper, we used a Bayesian approach to estimate the var model to solve the problem of too many parameters and too few samples in multivariate model. Unlike classical estimation methods, the basic idea of Bayesian estimation methods is to treat the parameters of the model to be estimated as random variables and obey a certain distribution, and then empirically give the prior distribution of the parameters to be estimated and combine it with the sample information. Bayes’ theorem can be used to calculate the posterior distribution of the parameter to be estimated, resulting in an estimate with the estimated parameter (Ma et al., 2021). We assume that the VAR model does not contain a constant term, the model can be written in the following form:
where \( a_{ijk} \) indicates the coefficient of the \( k \)-th order lag term \( y_j \) of the variable \( y_{j-t-k} \) in the \( i \)-th equation. If the random parameter \( a_{ijk} \) follows a normal distribution with mean \( \delta_{ijk} \) and variance \( S_{ijk}^2 \), then the number of hyperparameters to be determined in the var model (3) is at least \( 2N^2d \), with \( N^2d \) prior means and \( N^2d \) prior variances. Without considering the desirability of a priori information, it is quite complicated to reasonably assign the values of these \( 2N^2d \) hyperparameters in general. Therefore, it is necessary to find ways to reduce the number of hyperparameters that need to be assigned, to determine reasonable values of hyperparameters, and to improve the predictive capability of the model. In setting the prior distributions, we follow standard practice and use the procedure developed in Litterman (1986) with modifications proposed by Kadiyala and Karlsson (1997) and Sims and Zha (1998). The Minnesota prior distribution is an effective method to solve this problem, and its basic assumptions include the following aspects:

1. **Normality:** \( \epsilon_i = (\epsilon_1, \epsilon_2, \ldots, \epsilon_N) \sim \mathcal{N}_N (0, \Sigma) \).
2. **Independence:** the covariance matrix \( \Sigma \) and the model coefficient \( a_{ijk} \) are independent of each other.
3. **The prior distribution of the covariance matrix \( \Sigma \) is taken as the diffusion distribution:**
   \[
   \pi (\Sigma) \propto |\Sigma|^{-(N+1)/2}, \sigma > 0
   \]
4. **The Model coefficients are mutually independent and obey normal distribution:**
   \[
   a_{ijk} \sim \mathcal{N} (\delta_{ijk}, S_{ijk}^2)
   \]
5. **The mean value \( \delta_{ijk} \) is determined according to the following formula:**
   \[
   \delta_{ijk} = \begin{cases} 
   1, & i = j, k = 1, \\
   0, & \text{otherwise},
   \end{cases}
   \]
6. **The standard deviation \( S_{ijk} \) can be decomposed as the product of four factors:**
   \[
   S_{ijk} = \gamma \cdot g(k) \cdot f(i, j) \cdot \frac{S_i}{S_j}
   \]
   where \( \gamma \) denotes the overall tightness, the magnitude of its value reflects the degree of confidence the analyst has in the prior information, and a smaller value of \( \gamma \) represents a greater certainty of the prior information; \( g(k) \) is the tightness of the \( r \)-th order lagged variable relative to the first-order variable, which indicates the reduction in the usefulness of past information over current information; \( f(i, j) \) is the tightness of the \( j \)-th variable in the \( i \)-th equation relative to the \( i \)-th variable, and \( S_i \) is the standard deviation of the univariate autoregressive model for variable \( y_i \), and \( S_j \) is the standard deviation of the univariate autoregressive model for variable \( y_j \).

To facilitate the derivation, equation(3) can be written as a system of multivariate regressions:

\[
Y = X\beta + \epsilon, \quad \epsilon \sim \mathcal{N} (0, \Sigma \otimes I_n)
\]  

The Minnesota Priori shorthand for the model parameters is given as:

\[
(\beta | \Sigma) \sim \mathcal{N} (\mu_0, M_0), \quad \pi (\Sigma) \propto |\Sigma|^{-(N+1)/2}
\]

where \( \mu_0 \) is equal to 0 or 1, \( M_0 \) consists of \( T \) diagonal matrices. According to the Bayesian theorem, under the Minnesota prior distribution condition, the joint posterior distribution density function of the parameter \( (\beta, \Sigma) \) is:

\[
\pi (\beta, \Sigma | Y, X) \propto \frac{1}{|\Sigma|^{(N+T+1)/2}} \exp \left\{ -\frac{1}{2} \left[ (Y - X\beta)^T (\Sigma \otimes I_n)^{-1} (Y - X\beta) + (\beta - \mu_0)^T M_0^{-1} (\beta - \mu_0) \right] \right\}
\]

\[
\propto \frac{1}{|\Sigma|^{(N+T+1)/2}} \exp \left\{ -\frac{1}{2} \left[ (\beta - \beta^*)_T V^{-1} (\beta - \beta^*) - Y^T (\Sigma^{-1} \otimes I_n)^{-1} Y + \beta^*_T M_0^{-1} \beta^* \right] \right\}
\]

where \( \beta^* \) indicates the coefficient of the \( k \)-th order lag term \( y_j \) of the variable \( y_{j-t-k} \) in the \( i \)-th equation.

To facilitate the derivation, equation(3) can be written as a system of multivariate regressions:

\[
Y = X\beta + \epsilon, \quad \epsilon \sim \mathcal{N} (0, \Sigma \otimes I_n)
\]  

The Minnesota Priori shorthand for the model parameters is given as:

\[
(\beta | \Sigma) \sim \mathcal{N} (\mu_0, M_0), \quad \pi (\Sigma) \propto |\Sigma|^{-(N+1)/2}
\]

where \( \mu_0 \) is equal to 0 or 1, \( M_0 \) consists of \( T \) diagonal matrices. According to the Bayesian theorem, under the Minnesota prior distribution condition, the joint posterior distribution density function of the parameter \( (\beta, \Sigma) \) is:

\[
\pi (\beta, \Sigma | Y, X) \propto \frac{1}{|\Sigma|^{(N+T+1)/2}} \exp \left\{ -\frac{1}{2} \left[ (Y - X\beta)^T (\Sigma \otimes I_n)^{-1} (Y - X\beta) + (\beta - \mu_0)^T M_0^{-1} (\beta - \mu_0) \right] \right\}
\]

\[
\propto \frac{1}{|\Sigma|^{(N+T+1)/2}} \exp \left\{ -\frac{1}{2} \left[ (\beta - \beta^*)_T V^{-1} (\beta - \beta^*) - Y^T (\Sigma^{-1} \otimes I_n)^{-1} Y + \beta^*_T M_0^{-1} \beta^* \right] \right\}
\]
where

$$\beta_B = V^{-1} \left[ X^T (\Sigma \otimes I_n)^{-1} Y + M_0^{-1} \beta_0 \right]$$

$$V = [X^T (\Sigma \otimes I_n)^{-1} X + M_0^{-1}]^{-1}$$

Obviously, for a given covariance matrix $\Sigma$, the conditional posterior distribution of $\beta$ is a multivariate normal-terminus distribution with mean $\beta_B$ and variance matrix $V$.

$$\beta \mid \Sigma; Y, X) \sim \mathcal{N}(\beta_B, V)$$ (8)

4. Results and discussion

The results of the BVAR model was estimated by Eviews 8.0 software based on the transport annual report data for Beijing from 2003 to 2020, and we built a VAR model as a comparison.

4.1. Model comparison results

Whether VAR or BVAR model, the number of lags included needs to be selected. Based on the same data, the lag order selection criteria for the VAR model were the same as the BVAR model. As shown in Table 2, the optimal lag order was determined to order 1 in the VAR and BVAR models according to the five lag order evaluation indicators of $LR$ (Reinsel and Ahn, 1992), $FPE$ (Lütkepohl, 2005), $AIC$ (Akaike, 1974), $SIC$ (Neath and Cavanaugh, 1997) and $HQIC$ (Hannan and Quinn, 1979).

| Log | LogL | LR | FPE | AIC | SIC | HQIC |
|-----|------|----|-----|-----|-----|------|
| 0   | 124.94 | NA | $2.22 \times 10^{-15}$ | -13.88 | -13.53 | -13.84 |
| 1   | 246.48 | 128.68* | $7.68 \times 10^{-19*}$ | -22.41* | -19.66* | -22.14* |

* indicates lag order selected by the criterion. $LR$: sequential modified LR test statistic (each test at 5% level). $FPE$: Final prediction error. $AIC$: Akaike information criterion. $SIC$: Schwarz information criterion. $HQIC$: Hannan-Quinn information criterion.

The stability test of the model is necessary for the credibility of the parameter estimates (Lütkepohl, 2013). Before analysing the parameter estimation results, we determined the stability of the models. Figure 2 reveals the stability test results of VAR and BVAR models. As shown in Figure (a), the stability test results of the VAR model had a root that was not within the unit circle, the results were unstable and the parameter estimation results cannot be used in the analysis results; as shown in Figure (b), the stability test results of the BVAR model were all within the unit circle, the parameter estimation results are plausible and can be used in the analysis results. Accordingly, in this study, the BVAR(1) model is more suitable to analysis the urban macroeconomic and transport factors of traffic accidents than VAR(1) model.

4.2. Model estimation results and discussion

4.2.1. Overall estimation results

Given the fact that 1 lag was used in the estimation of the BVAR, the equations can be presented in an easy-to-read format, as in Table 2, each column represents an autoregressive equation in one variable. As shown in Table 2, most of the autoregressive equations had R-squared values close to 1, and with standard errors close to 0, the model results were plausible. In overall terms, the parameter estimation results revealed that the number of traffic accidents were affected by all relevant indicators in this study. It has been noted that the coefficients in the parameter estimation results of BVAR are not indicative of the system behaviour, as such, impulse responses need to be examined to reach more concrete conclusions (Michail and Melas, 2020).

Impulse response analysis is the tool which have been proposed for disentangling the relations between the variables in a VAR model (Lütkepohl, 2013). From the study by Li et al. (2019), it can be inferred that a variable is considered to increase the number of traffic accidents if the majority of its cumulative impulse response is greater than zero, conversely if the majority of the cumulative impulse response is less than zero, the variable is considered to reduce the
Bayesian vector autoregressive analysis

![Graphs](image)

(a) Inverse Roots of VAR Characteristic Polynomial  
(b) Inverse Roots of BVAR Characteristic Polynomial

**Figure 2:** Model Stability Determination Criteria

|                | 1   | 2    | 3     | 4     | 5   | 6    | 7     |
|----------------|-----|------|-------|-------|-----|------|-------|
| **Accidents**  | 0.66| -0.14| 0.03  | 0.06  | -0.28| 0.09 | 0.76  |
| **Population** | 0.08| 0.71 | -0.13 | 0.63  | -0.46| 0.35 | 0.11  |
| **GDP**        | 0.11| -0.12| 0.67  | 0.28  | 0.79 | 0.36 | 0.45  |
| **Ownership of Private Vehicle** | -0.06| 0.50 | -0.04 | 0.26  | 0.28 | 0.19 | 0.22  |
| **Ownership of bus** | 0.15| 0.14 | 0.21  | 0.34  | -0.02| 0.10 | -0.04 |
| **Subway Rail** | -0.27| -0.30| 0.37  | -0.48 | 0.15 | 0.17 | 0.53  |
| **Road Average Speed** | 0.15| 0.06 | -0.04 | 0.03  | -0.02| 0.05 | 0.19  |
| **c**          | -0.03| 0.08 | 0.04  | 0.02  | 0.34 | -0.11| -0.12 |
| **R-squared**  | 0.95| 0.99 | 0.99  | 0.97  | 0.95 | 0.99 | 0.74  |
| **S.E equation** | 0.06| 0.05 | 0.03  | 0.07  | 0.07 | 0.04 | 0.15  |

Table 3  
BVAR model parameter estimation results

Concerning the population variable, the impulse response of accidents increased from 0 and reached a maximum value in period 2, then decreased rapidly to zero in period 10, and levelled off in period 13 and was greater than zero. These results suggest that population increase had the potential to increase the number of traffic accidents in the short term. A possible explanation for this might be that an increase in urban population would lead to an increase in travel demand, which could further increase the incidence of road traffic accidents. Lee et al. (2008) disclaimed that the rapid increase of travel demand may influence on the high rates of traffic accident. These results are in accord with recent study in Zhongshan, China on demographic characteristics and traffic accidents indicating that population has a significant positive influence on traffic accidents (Wu et al., 2020).

In terms of the GDP variable, the impulse response of accident was also 0 in period 1, decreased to minimum in period 5, then increased and stabilized in period 30 and was consistently less than 0. These results indicate that the increase in GDP could reduce the number of traffic accidents, and the effect would last for a long time. These results are contrary to the findings of a study in Algeria which indicated that that the number of traffic accidents in Algeria is positively influenced by the GDP per capita in the short and long term (Bougueroua and Carnis, 2016). This inconsistency may be due to that, in Algeria, GDP growth has led to an increase in private motor vehicles, which...
will increase the frequency of traffic accidents, whereas in Beijing, GDP growth has led to an improvement in public transport facilities and traffic safety facilities, which will reduce the risk of traffic accidents. Some studies also claimed that the increase of GDP has negative impacts on the number of fatalities in high-income countries, but it behaves oppositely in low-income countries (Van Beeck et al., 2000; Bener et al., 2011; Yusuff, 2015).

4.2.3. Macro-transport factors

Regarding the road average speed, we found that the impulse response of road traffic accidents was zero in the current period, then increased and reached a maximum in period 2, then began to decrease, and then stabilized and converged to 0 in period 20. In addition, this impulse response was mostly greater than zero in and greater than the other variables throughout the variation. These results show that an increase in the average speed of vehicles on urban roads might increase the frequency of urban accidents, and in the six variables of this model, average road speed had the greatest positive impact on traffic accidents, and the effects last for a long time. It seems possible that these results are due to that the increase in speed will reduce the driver’s reaction time before an accident occurs, which will increase the risk of an accident occurring. These are consistent with the findings of numerous studies analysing the correlation between vehicle speed and traffic accidents, with studies such as Aljanahi et al. (1999), Elvik (2013) and Sugiyanto and Malkhamah (2018) all pointed out that an increase in vehicle speed increases the risk of traffic accidents. Therefore, speed limits are one of the effective means to reduce urban traffic accidents.

We found the impulse response of accident to private vehicle ownership was zero in period 1, increased to a maximum in period 2, then decreased and stabilized to 0 in period 15. Furthermore, the majority of the impulse response was greater than zero and only lower than road average speed. From these results, it can be inferred that the increase in private vehicles ownership had a positive effect on urban traffic accidents, and the magnitude of this effect was second only to that of road average speed. Similar to population factors, a possible reason for these results is that an increase in private motor vehicles increases the demand for road traffic and, in turn, the incidence of accidents.
These results further support the idea of traffic safety impact analysis in Hong Kong that the growth of private vehicle ownership will increase the rate of traffic accidents (Li et al., 2018). Consequently, controlling the number of private motor vehicles plays an important role in reducing the number of urban traffic accidents.

With respect to subway rail mileage, the impulse response was also 0 in period 1, dropped to a minimum in period 2, then rose and stabilized in period 7, and converged to 0 approximately in period 50. This impulse response was the lowest response of six variables and mostly less than zero. These results provide important insights that the increase in subway rail mileage could reduce the number of traffic accidents, although the impact would diminish over time, their duration was long. Meanwhile the negative impact of subway rail mileage on traffic accidents was greater than other factors. These results are likely to be related to the traffic demand which shifts from roads to urban rail due to increased subway rail mileage. This finding broadly supports the work of other studies in this area linking subway rail mileage with urban traffic accidents, for instance, Litman (2004, 2005) stated that increased rail transit will reduce traffic accidents rates, traffic injuries and fatalities, and Mohapatra (2015) also indicated that rail transit can reduce the urban traffic accidents.

About the bus ownership, the accidents impulse response decreased from 0 to minimum in period 3 and 4, then increased and stabilized in period 20 and was consistently less than 0. These results show that an increase in bus ownership was considered to reduce the number of traffic accidents, and similar to the subway rail mileage, although this negative effect diminished over this time, it persisted for a long period. It is difficult to explain this result, but the possible reason is that the road bus systems are more efficient and safer to transport than private transport systems, the improving of road bus system would shift the demand for private transport towards it, therefore may reduce the number of traffic accidents. Similar findings are also evidenced by previous studies. For example, a report of Duduta et al. (2015) revealed that high quality bus systems can improve the traffic safety, Tiwari et al. (2016) also pointed out that improving public transport infrastructure can enhance urban traffic safety.

5. Conclusion and future directions

This paper simultaneously explored the dynamic relationship between the macro-level economic and transport factors and urban traffic accidents. Based on a small sample size transport annual report data for Beijing, a BVAR model was developed to examine the contribution of six economic and transport variables, including GDP, population, private vehicle ownership, bus ownership, subway rail mileage and road average speed to the number of traffic accidents.

The BVAR approach showed validities to explicitly explore the small sample size time series data structure in traffic safety field. The results confirmed that long-term or short-term relationships existed between the macro-level economic and transport factors and the number of urban traffic accidents. About macroeconomic factors, population growth might lead to an increase in the number of traffic accidents in the short term, while GDP growth had a negative long-term impact on the number of traffic accidents. In terms of macro-transport factors, urban metro rail mileage and bus ownership had a long-term negative effect on the number of traffic accidents, and subway rail mileage had the largest negative effect on the number of traffic accidents. Increases in average road speed and private motor vehicle ownership had the potential to increase traffic accidents, with average road speed had the largest positive effect on the number of traffic accidents over a longer period of time. The relevant government departments can reduce road traffic accidents by increasing economic investment in the construction of public transport facilities, limiting investment in private transport facilities and limiting road speed when formulating urban development direction and management policies.

The analysis of the factors influencing traffic accidents in this paper has not yet considered the relationship between economic factors and transportation factors at the macro-level. In the future, the introduction of urban investment in transport facilities as an influencing factor can be considered to further analyse the influence process of macro-level economic and transport factors on traffic accidents.

References

Akaike, H., 1974. A new look at the statistical model identification. IEEE transactions on automatic control 19, 716–723.
Aljanahi, A., Rhodes, A., Metcalfe, A.V., 1999. Speed, speed limits and road traffic accidents under free flow conditions. Accident Analysis & Prevention 31, 161–168.
Almeida, R.L.F.d., Bezerra, J.G., Braga, J.U., Magalhães, F.B., Macedo, M.C.M., Silva, K.A., 2013. Man, road and vehicle: risk factors associated with the severity of traffic accidents. Revista de saude publica 47, 718–731.
Apparao, G., Mallikarjunareddy, P., Raju, S., 2013. Identification of accident black spots for national highway using gis. International Journal of Scientific & Technology Research 2, 154–157.
Bener, A., Yousif, A., Al-Malki, M., El-Jack, I., Bener, M., 2011. Is road traffic fatalities affected by economic growth and urbanization development? Advances in transportation studies.

Bougueroua, M., Carnis, L., 2016. Economic development, mobility and traffic accidents in algeria. Accident Analysis & Prevention 92, 168–174.

Delong, D.N., Ingram, B.F., Whiteman, C.H., 2000. A bayesian approach to dynamic macroeconomics. Journal of Econometrics 98, 203–223.

Duduta, N., Adriaizola-Stiel, C., Hidalgo, D., John, V., Wass, C., et al., 2015. Traffic safety on bus priority systems. Elvik, R., 2013. A re-parameterisation of the power model of the relationship between the speed of traffic and the number of accidents and accident victims. Accident Analysis & Prevention 50, 854–860.

Gang, W., 2019. Safety evaluation model for smart driverless car using support vector machine. Journal of Intelligent & Fuzzy Systems 37, 433–440.

Ghasedi, M., Sarfjoo, M., Bargegol, L., 2021. Prediction and analysis of the severity and number of suburban accidents using logit model, factor analysis and machine learning: a case study in a developing country. SN Applied Sciences 3, 1–16.

Giannone, D., Lenza, M., Momferatou, D., Onorante, L., 2014. Short-term inflation projections: A bayesian vector autoregressive approach. International journal of forecasting 30, 635–644.

Hannan, E.J., Quinn, B.G., 1979. The determination of the order of an autoregression. Journal of the Royal Statistical Society: Series B (Methodological) 41, 190–195.

Iwata, K., et al., 2010. The relationship between traffic accidents and economic growth in china. Economics Bulletin 30, 3306–3314.

Kadiyala, K.R., Karlsson, S., 1997. Numerical methods for estimation and inference in bayesian var-models. Journal of Applied Econometrics 12, 99–132.

Lankarani, K.B., Heydari, S.T., Aghabeigi, M.R., Moafian, G., Hoseinzadeh, A., Vossoughi, M., 2014. The impact of environmental factors on traffic accidents in iran. Journal of injury and violence research 6, 64.

Lee, J.Y., Chung, J.H., Son, B.S., 2008. Analysis of traffic accident severity for korean highway using structural equations model. Journal of Korean Society of Transportation 26, 17–24.

Li, X., Wu, L., Yang, X., 2018. Exploring the impact of social economic variables on traffic safety performance in hong kong: A time series analysis. Safety science 109, 67–75.

Li, Z., Yu, H., Zhang, G., Wang, J., 2019. A bayesian vector autoregression-based data analytics approach to enable irregularly-spaced mixed-frequency traffic collision data imputation with missing values. Transportation Research Part C: Emerging Technologies 108, 302–319.

Littman, T., 2004. Rail transit in america. A Comprehensive Evaluation of Benefits: Victoria Transport Policy Institute: Victoria, BC, Canada.

Littman, T., 2005. Impacts of rail transit on the performance of a transportation system. Transportation Research Record 1930, 23–29.

Litman, R.B., 1986. Forecasting with bayesian vector autoregressions—five years of experience. Journal of Business & Economic Statistics 4, 25–38.

Liu, Z., He, J., Zhang, C., Xing, L., Zhou, B., 2020. The impact of road alignment characteristics on different types of traffic accidents. Journal of Transportation Safety & Security 12, 697–726.

Lütkepohl, H., 2005. New introduction to multiple time series analysis. Springer Science & Business Media.

Lütkepohl, H., 2013. Vector autoregressive models, in: Handbook of research methods and applications in empirical macroeconomics. Edward Elgar Publishing.

Ma, J., Shang, Y., Zhang, H., 2021. Application of bayesian vector autoregressive model in regional economic forecast. Complexity 2021.

Michaillaki, P., Quddus, M., Pittfield, D., Huetson, A., 2016. A time-series analysis of motorway collisions in england considering road infrastructure, socio-demographics, traffic and weather characteristics. Journal of Transport & Health 3, 9–20.

Mohapatra, D., 2015. An economic analysis of light rail transit in addis ababa ethiopia. European Academic Research 3, 3114–3144.

Najaf, P., Thill, J.C., Zhang, W., Fields, M.G., 2018. City-level urban form and traffic safety: A structural equation modeling analysis of direct and indirect effects. Journal of transport geography 69, 257–270.

Neath, A.A., Cavanaugh, J.E., 1997. Regression and time series model selection using variants of the schwarz information criterion. Communications in Statistics-Theory and Methods 26, 559–580.

Ni, S., Sun, D., 2005. Bayesian estimates for vector autoregressive models. Journal of Business & Economic Statistics 23, 103–117.

Qu, S., Wang, W., Man, J., Gu, Z., Yang, J., Chu, D., 2019. Curve speed modeling and factor analysis considering vehicle-road coupling effect, in: 2019 5th International Conference on Transportation Information and Safety (ICITIS), IEEE. pp. 1127–1131.

Reinsel, G.C., Ahn, S.K., 1992. Vector autoregressive models with unit roots and reduced rank structure: Estimation, likelihood ratio test, and forecasting. Journal of time series analysis 13, 353–375.

Sims, C.A., 1980. Macroeconomics and reality. Econometrica: journal of the Econometric Society , 1–48.

Sims, C.A., Zha, T., 1998. Bayesian methods for dynamic multivariate models. International Economic Review, 949–968.

Srirajudeen, A.O., Law, T.H., Wong, S.V., Jakarni, F.M., Ng, C.P., 2021. The sources of the kuznets relationship between the road deaths to road injuries ratio and economic growth. Journal of safety research 78, 262–269.

Soehodho, S., 2017. Public transportation development and traffic accident prevention in indonesia. IATSS research 40, 76–80.

Sugiyanto, G., Malkhamah, S., 2018. Determining the maximum speed limit in urban road to increase traffic safety. Jurnal Teknologi 80.

Sun, L.L., Liu, D., Chen, T., He, M.T., 2019. Road traffic safety: An analysis of the cross-effects of economic, road and population factors. Chinese journal of traumatology 22, 290–295.

Tiwari, G., Jain, D., Rao, K.R., 2016. Impact of public transport and non-motorized transport infrastructure on travel mode shares, energy, emissions and safety: Case of indian cities. Transportation research part D: transport and environment 44, 277–291.

Van Beeck, E.F., Borsboom, G.J., Mackenbach, J.P., 2000. Economic development and traffic accident mortality in the industrialized world, 1962–1990. International journal of epidemiology 29, 503–509.

Wang, C., Quddus, M., Ison, S., 2009. The effects of area-wide road speed and curvature on traffic casualties in england. Journal of transport geography 17, 385–395.
World Health Organization, 2021. Road traffic injuries. Retrieved from: https://www.who.int/news-room/fact-sheets/detail/road-traffic-injuries, Last accessed on June 21, 2021.

Wu, W., Jiang, S., Liu, R., Jin, W., Ma, C., 2020. Economic development, demographic characteristics, road network and traffic accidents in Zhongshan, China: gradient boosting decision tree model. Transportmetrica A: transport science 16, 359–387.

Yusuff, M.A., 2015. Impact assessment of road traffic accidents on Nigerian economy. Journal of Research in Humanities and Social Science 3, 8–16.

Zhang, Y., Jing, L., Sun, C., Fang, J., Feng, Y., 2019. Human factors related to major road traffic accidents in China. Traffic injury prevention 20, 796–800.