UNIVERSITÀ DEGLI STUDI DELLA TUSCIA

DEPARTMENT OF ECONOMICS, ENGINEERING SOCIETY AND BUSINESS ORGANIZATION

ECONOMETRIC PERSPECTIVES IN CIRCULAR ECONOMY

TOPIC:

HANOI'S MOTORBIKE BAN FOR SUSTAINABLE WELL-BEING

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ACKNOWLEDGMENTS AND COMMITMENT

Sincere appreciation is extend to Professor Luca Secondi for invaluable guidance in **Econometric Perspectives in Circular Economy.** The expertise and dedication shared have greatly enriched the understanding of the subject, inspiring a rigorous and insightful approach to sustainable economic models. I also gratefully acknowledge the Open Science Framework for providing access to the necessary database.

Futhermore, I declare that this work on *"Hanoi's Motorbike Ban for Sustainable Well-being"* has not been submitted previously, in whole or in part, for any degree or qualification at this or any other institution.

I take full responsibility for the truthfulness and originality of this reseach work.

Declarant

Pham Nhat Minh Tran

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ABSTRACT

Rapid urban growth, as seen in cities like Hanoi – the capital of Vietnam, is outstripping the development of formal infrastructure needed to support the increasing population. The situation is worsened by the rise of informal transportation systems that appear in spontaneously developed urban areas. Motorbikes serve as the main means of transportation for most people in Hanoi. To provide context, data from 2024 indicated 2.9 million units sold, marking a 4.9% compared to the previous year (MCD Team, 2025). A proposed solution involves banning motorbikes from specific areas. Nevertheless, given their widespread current use, a future ban's effectiveness will require public backing. Consequently, this project aimed to create statistical model of transport attitudes and behaviors regarding a potential ban, enabling to predict the effects of different transport policies and understand the reasons behind travel choices.

CHAPTER 1: INTRODUCTION

1.1. Urgency of the study

Hanoi, a city deeply reliant on motorbike for daily transportation, faces growing environmental and urban challenges. The proposed motorbike ban is a critical policy measure aimed at improving air quality, reducing congestion, and fostering a more sustainable urban landscape. The necessity of this research lies in serveral key areas:

Environmental Impact: Hanoi struggles with severe air pollution, much which stems from motorbike emissions. A transition away from motorbikes could significantly decrease carbon emissions and improve public health.

Traffic Congestion & Urban Planning: The overwhelming number of motorbikes contributes to traffic inefficiencies, slowing economic productivity and reducing overall quality of life. The ban encourages a shift toward public transport, cycling, and pedestrian-friendly infrastructure.

Public Adaptation & Economic Considerations: The ban affect millions of residents who depend on motorbikes for daily mobility. Evaluating alternatives, affordability, and implementation strategies is essential to ensure a smooth transition without disrupting livelihoods

By addressing these urgent concerns, the research contributes to the broader discourse on sustainable urban mobility, environmental health, and inclusive policy-making. A thorough evaluation will help determine the feasibility and long-term impact of Hanoi’s motorbike ban, ensuring that sustainability goals align with public well-being.

1.2. Research scope

The research subjects were clearly defined as travel behavior by means of transport and views on the motorbike ban.

Scope:

- In terms of space: Research limitations in the Hanoi capital area
- In terms of time: Data collected from October to December 2023

1.3. Significance of the study

With this study, policy-maker can evaluate the residents' response if the law is enacted and what factors should be focused on to achieve the sustainable urban development and improving residents' lives.

CHAPTER 2: DATA ANALYSIS

2.1. Methodology

2.2.1. Data collection process

Data was collected through a survey with the following structures:

Variable name	*Type*	*Description*
opinion_ban	Binary	What is your opinion about motobikes ban policy?
freqpweek	Numeric	Frequency of your transport behavior
freq_car	Numeric	How many times do you use a car per week?
dist_to_pub	Continuous	What is the distance to the nearest bus or train stop from your home location
own_car	Numeric	Number of cars in your families
own_motob	Numeric	Number of motorbikes in your families
own_bike	Numeric	Number of bikes in your families
own_ebike	Numeric	Number of ebikes in your families
aware_ban	Categorical	Have you ever heard of the plan to ban motorbikes from a section of Hanoi central business district?

vehic	Categorical	Which vehicle do you use for transport purpose?
fut_veh	Categorical	Do you plan to own another vehicle in the near future, and what is that vehicle?

Figure 1: Variables Table

Eleven variables correspond to eleven columns in the dataset, containing approximately 20,000 observations about transport behavior of Hanoi residents. Most of the data represented is categorical or numeric.

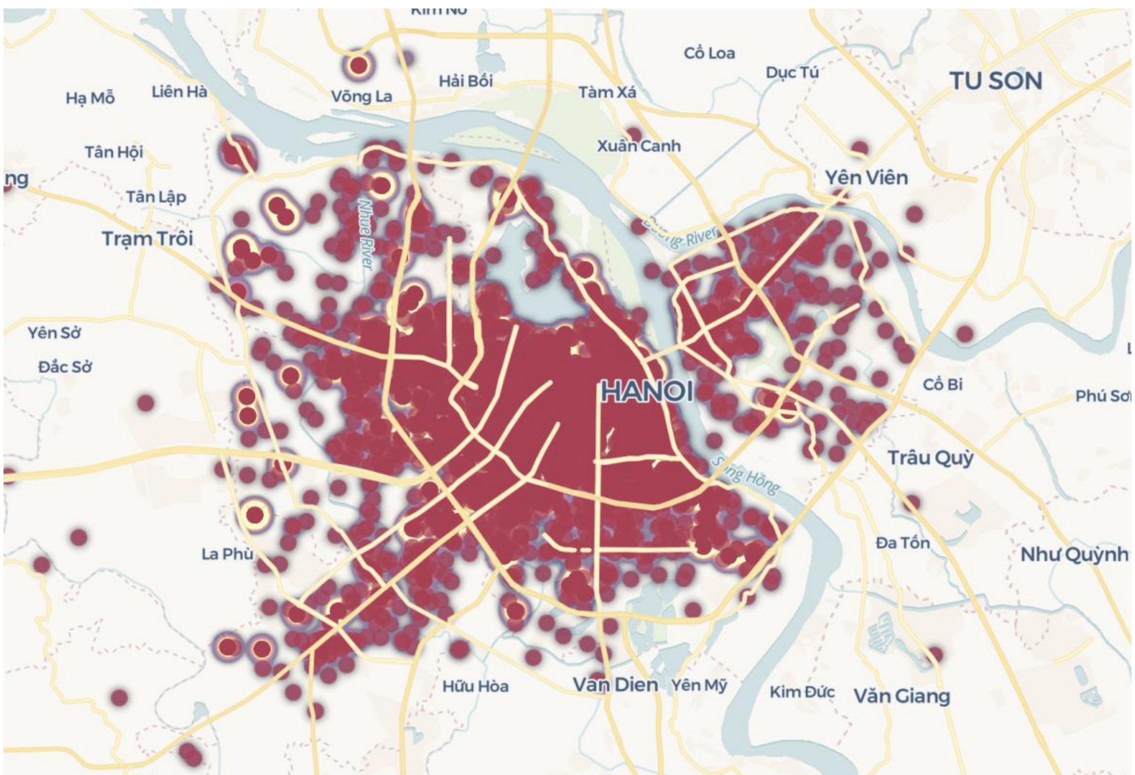

Figure 2: Traffic density map in central districts of Hanoi

2.2.2. Data analysis methods

Define the dependent variablea as **opinion_ban** with binary data type. Using binary logistic regression for analyzing because the outcome is binary: a categorical variable with exactly two possible values.

$$P_i = E(Y = 1/X) = \frac{e^{(B_0 + B_1X_1 + B_2X_2 + \dots + B_kX_k)}}{1 + e^{(B_0 + B_1X_1 + B_2X_2 + \dots + B_kX_k)}}$$

Where:

- P = the probability that a case is in a particular category
- X = Independent variables.
- B = the coefficient of the predictor.

The odds ratio (OR), estimates the change in the odds of membership in the target group for a one unit increase in the predictor. It is calculated by using the regression coefficient of the predictor as the exponent (Agresti, 1996).

2.2. Data Visualization

2.2.1. People opinion on travel modes

- At the vehicle ownership:

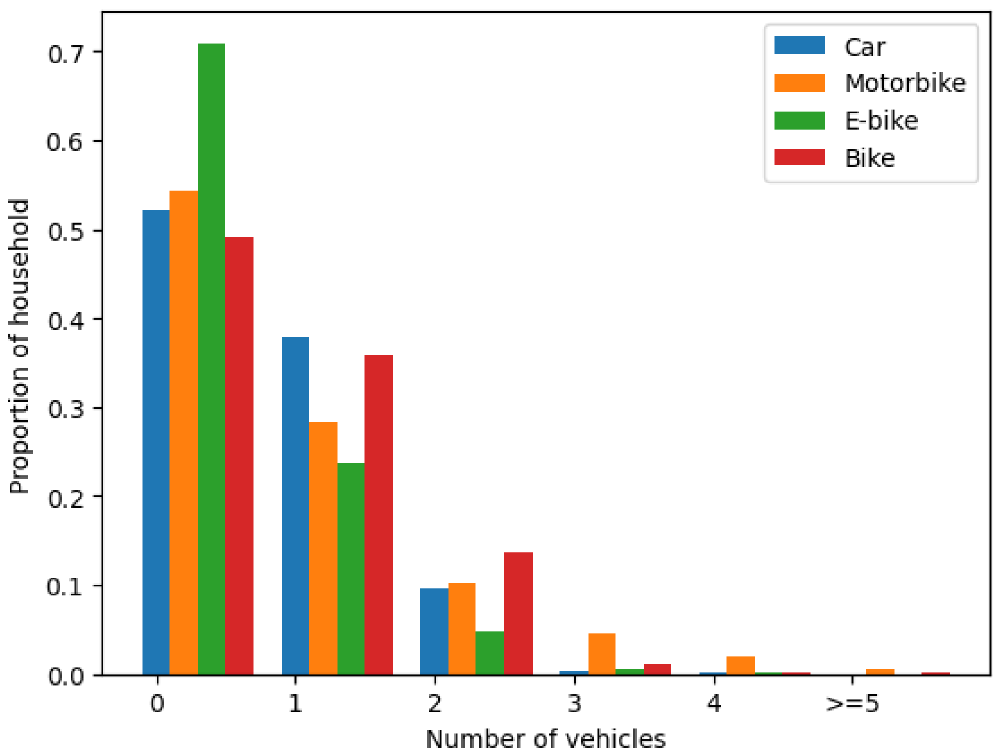

Figure 3: Vehicle ownership / Household

Motorbikes dominate Hanoi areas due to affordability and maneuverability while cars are witnessed a low proportion due to high costs, parking limitations, and road conditions. In addition, e-bikes indicate a shift toward eco-friendly transport.

- Bus opinion distribution by ban attitude:

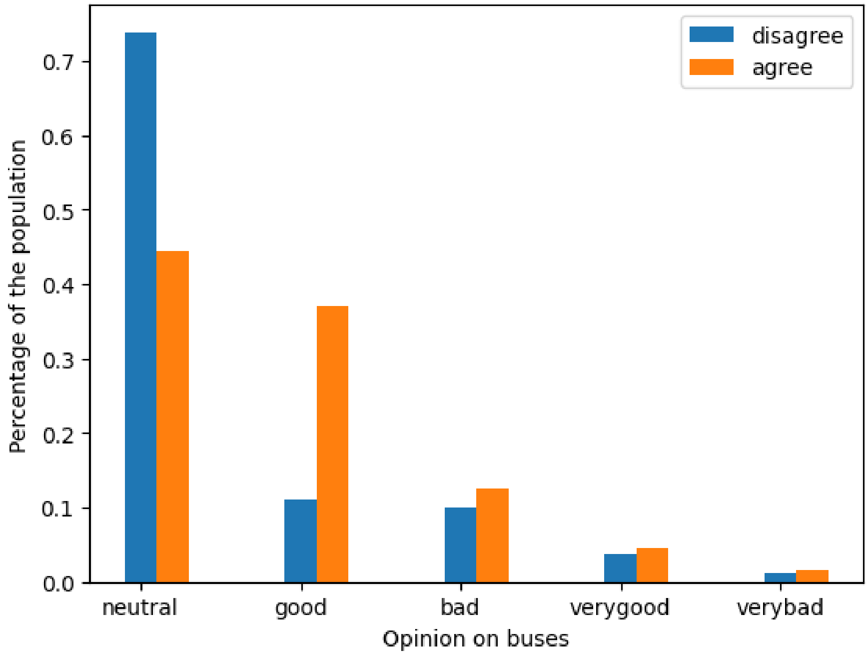

Figure 4: Bus opinion distribution by ban attitude

People who are neutral on buses are also quite likely to not agree with the ban. In contrast, who thinks buses are good most likely to agree with the ban.

- Car opinion distribution by ban attitude:

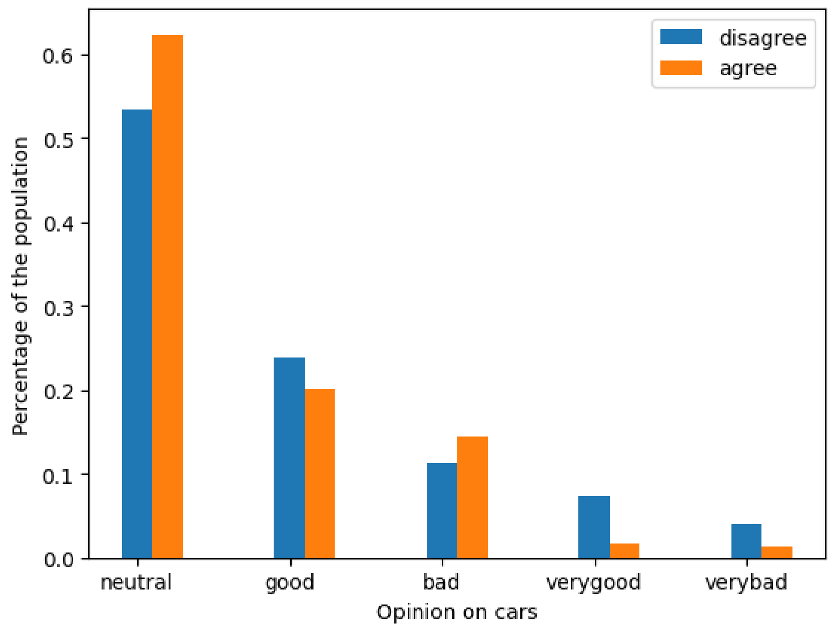

Figure 5: Car opinion distribution by ban attitude

People who are neutral on cars are likely disagree with the ban while people who thinks cars are very good strongly agree with the ban.

- Motobike opinion distribution by ban attitude:

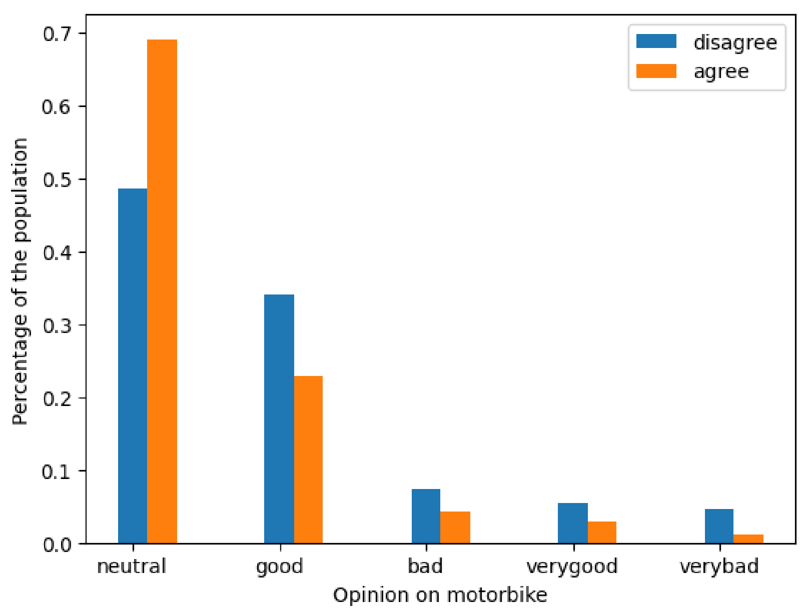

Figure 6: Motobike opinion distribution by ban attitude

People who thinks that motorbike are good tend to disagree with the ban.

2.2.2. Descriptive analysis

Core variable: **opinion_ban**. This is a binary variable indicating whether a respondent disagree (0) or agree (1) a motorbike ban policy.

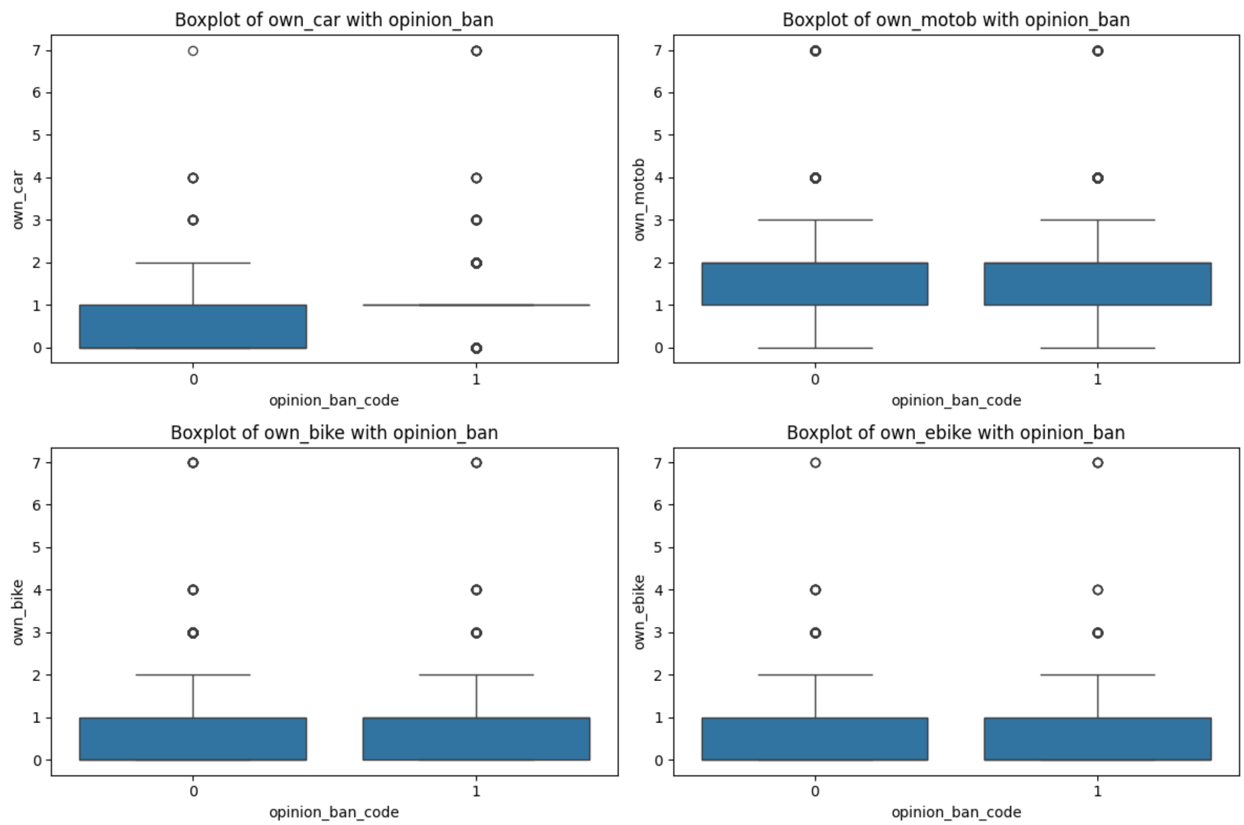

Figure 7: Boxplot of four variables with opinion_ban

Variable	Group	Mean	Median	Mode	Std Dev	Skewness
own_car	0	0.45	0.00	0	0.57	1.25
	1	0.92	1.00	1	0.63	0.74
own_motob	0	1.84	2.00	2	1.04	1.33
	1	1.80	2.00	2	0.74	1.01
own_bike	0	0.49	0.00	0	0.75	2.31
	1	0.74	1.00	0	0.77	0.88

own_ebike	0	0.36	0.00	0	0.64	2.17
	1	0.31	0.00	0	0.56	2.30

own_car: Those who support the ban tend to own more cars (Mean = 0.92) than those who oppose it (Mean = 0.45). The distribution for both groups is skewed right (positive skewness).

own_motob: Motorcycle ownership is slightly higher among opponents, but both groups have similar medians and modes. The higher skewness in the support group indicates a more concentrated distribution.

own_bike: People who support the ban tend to own more bikes on average (Mean = 0.74 vs. 0.49). Opponents show a highly skewed and peaked distribution, suggesting that most own no bike.

own_ebike: Both groups mostly don't own e-bikes (Median = 0), but opponents have a slightly higher average ownership. High skewness indicates strong right-skewed distributions with rare higher values.

2.2. EDA

2.2.1. Objective

This analysis aims to explore the relationship between ownership of various types of vehicles and individuals' opinions on a proposed ban, represented by the binary variable **opinion_ban** (0 = disagree , 1 = agree).

2.2.2. Correlation Analysis

Examine the correlation between **opinion_ban** (0 = disagree , 1 = agree) and each of the following variables: **own_car, own_motob, own_bike, and own_ebike.**

The hypothesis is given:

H_0: There is no association between opinion_ban_code and the selected variable. ($r=0$)

H_1: There is a association between opinion_ban_code and the selected variable. ($r \neq 0$)

The results are:

```
Correlation of opinion_ban and own_car: 0.3539, P-value: 0.0000
Correlation of opinion_ban and own_motob: -0.0233, P-value: 0.0010
Correlation of opinion_ban and own_bike: 0.1625, P-value: 0.0000
Correlation of opinion_ban and own_ebike: -0.0460, P-value: 0.0000
```

All selected variables have p – value < 0.05. Therefore, reject null hypothesis, there is evidence of a association. **own_car** has a moderate positive correlation with **opinion_ban**, **own_motob** has a very weak negative correlation also with **own_bike** and **own_ebike.**

2.2.3. Hypothesis testing

Since the count variables (**own_**) are not normally distributed (as seen from boxplots), the test used is Mann – Whitney U test (non – parametric test) instead of a t – test to compare the medians between the two groups (Disagree and Agree)

General Hypotheses for each variable:

H_0: There is no difference in the distribution of vehicle ownership between the two opinion groups.

H_1: There is a difference in the distribution of vehicle ownership between the two opinion groups.

The results are:

```
own_car: Mann-Whitney U statistic = 27808386.50, p-value = 0.0000
own_motob: Mann-Whitney U statistic = 45317956.00, p-value = 0.0231
own_bike: Mann-Whitney U statistic = 36787340.00, p-value = 0.0000
own_ebike: Mann-Whitney U statistic = 47664040.00, p-value = 0.0000
```

For all tested variables, reject the null hypothesis at the 5% significane level, indicating that vehicle ownership significantly differs between individuals who support and those oppose the ban.

2.2.4. Multicollinearity

Using Variance Inflation Factor (VIF) to detect independent variables that are too highly correlated with each other. From there, propose measures to optimize the model.

```
Variance Inflation Factors
Minimum possible value = 1.0
Values > 10.0 may indicate a collinearity problem

     freqpweek    1.149
      freq_car    1.313
   dist_to_pub    1.013
       own_car    1.487
     own_motob    1.106
      own_bike    1.145
     own_ebike    1.173
  aware_ban_no    1.770
 aware_ban_yes    1.676
     vehic_bus    1.359
     vehic_car    5.702
   vehic_ebike    2.224
    vehic_moto    6.222
    vehic_taxi    1.285
    vehic_tram    1.010
    vehic_walk    1.438
   fut_veh_car    7.394
 fut_veh_ebike    2.295
  fut_veh_moto    5.487
    fut_veh_no    7.641
```

Figure 8: VIF Table

Generally, no variable has a VIF > 10, so there's no servere multicollinearity. However, some variables have VIF > 5, indicating moderate to high multicollinearity, which might affect the stability of regression coefficients.

2.3. Results and recommendations

2.3.1. Results table

```
Model 2: Logit, using observations 1-19807
Dependent variable: opinion_ban_code
Standard errors based on Hessian

                 coefficient   std. error      z       p-value
  -------------------------------------------------------------
  const          -0.765690     0.167921      -4.560    5.12e-06  ***
  freqpweek      -0.0468737    0.00465762   -10.06     7.98e-024 ***
  freq_car        0.299822     0.00779928    38.44     0.0000    ***
  dist_to_pub    -1.73352e-05  2.22985e-05   -0.7774   0.4369
  own_car         0.748505     0.0363801     20.57     4.64e-094 ***
  own_motob      -0.129485     0.0211477     -6.123    9.19e-010 ***
  own_bike        0.349349     0.0268376     13.02     9.77e-039 ***
  own_ebike      -0.356984     0.0340136    -10.50     9.08e-026 ***
  aware_ban_no    0.787260     0.0653841     12.04     2.18e-033 ***
  aware_ban_yes   1.88110      0.0533563     35.26     2.83e-272 ***
  vehic_bus      -0.402924     0.166126      -2.425    0.0153    **
  vehic_car       0.206983     0.112174       1.845    0.0650    *
  vehic_ebike     0.00804117   0.122861       0.06545  0.9478
  vehic_moto     -0.419274     0.103220      -4.062    4.87e-05  ***
  vehic_taxi     -0.0424605    0.181870      -0.2335   0.8154
  vehic_tram     -0.417036     0.917422      -0.4546   0.6494
  vehic_walk     -0.115971     0.152545      -0.7602   0.4471
  fut_veh_car    -0.429139     0.131402      -3.266    0.0011    ***
  fut_veh_ebike   0.238478     0.152196       1.567    0.1171
  fut_veh_moto   -0.360590     0.133018      -2.711    0.0067    ***
  fut_veh_no     -0.661277     0.130227      -5.078    3.82e-07  ***

Mean dependent var   0.622002   S.D. dependent var   0.484899
McFadden R-squared   0.301709   Adjusted R-squared   0.300110
Log-likelihood      -9171.025   Akaike criterion     18384.05
Schwarz criterion    18549.82   Hannan-Quinn         18438.31

Number of cases 'correctly predicted' = 15513 (78.3%)
f(beta'x) at mean of independent vars = 0.199
Likelihood ratio test: Chi-square(20) = 7925.02 [0.0000]

           Predicted
               0       1
  Actual 0   5466    2021
         1   2273   10047

Excluding the constant, p-value was highest for variable 13 (vehic_ebike)
```

Figure 9: Regression coefficients outcome

Dependent variable: **opinion_ban** (0 – disagree, 1 – agree).

Number of observations: 19,807.

McFadden's R – squared is 0.301709 => Reasonable explanatory power for social science data.

Likelihood ratio test: p – value: 0.000 => The model overall is statistically significant.

Variables with p - value < 0.05 are considered statistically significant predictors and to better intepretation results, it needs odds ratio transformation:

Variable	Coefficient	Odds Ratio	p-value	Interpretation
freqpweek	−0.0469	0.9542	<0.0001	Walking more often slightly decreases the odds of supporting the ban.
freq_car	0.2998	1.3494	<0.0001	More frequent car use increases the odds of support by ~35%.
own_car	0.7485	2.1135	<0.0001	Car owners are more than twice as likely to support the ban.
own_motob	−0.1295	0.8785	<0.0001	Motorcycle owners are less likely to support the ban.
own_bike	0.3493	1.4184	<0.0001	Bicycle owners are more likely to support the ban.
own_ebike	−0.3570	0.6996	<0.0001	E-bike owners are ~30% less likely to support the ban.
aware_ban_no	0.7873	2.1974	<0.0001	People aware of the ban (but not in favor) are more than twice as likely to support it.
aware_ban_yes	1.8811	6.5615	<0.0001	People who support the ban are over 6.5 times more likely to support it.
vehic_bus	−0.4029	0.6682	0.0153	Regular bus users are less likely to support the ban.

vehic_moto	−0.4193	0.6576	<0.0001	Motorbike users are less likely to support the ban.
fut_veh_car	−0.4291	0.6513	0.0011	Planning to buy a car reduces the odds of supporting the ban.
fut_veh_moto	−0.3606	0.6974	0.0067	Planning to buy a motorcycle also decreases odds of support.
fut_veh_no	−0.6613	0.5163	<0.0001	Not planning to buy any vehicle reduces support by ~48%.

From the above results tables, the chart of variables with their impact:

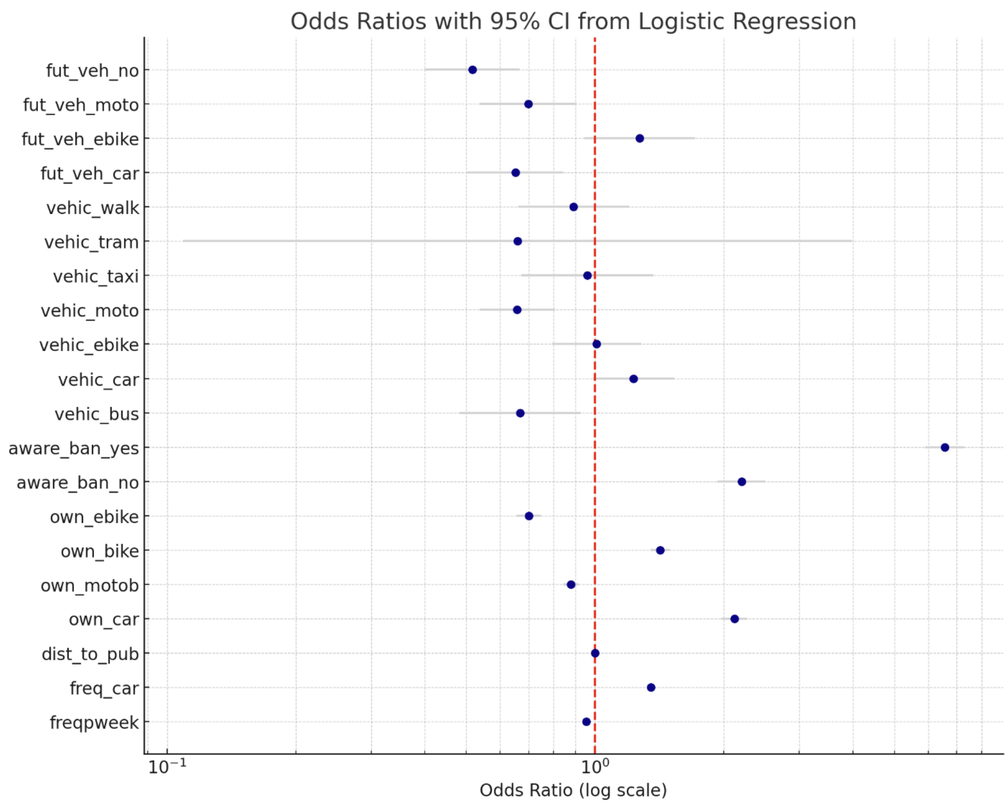

Figure 10: Variables with the largest impact

Generally:

Variable	Impact
aware_ban_yes	Very strong positive
fut_veh_no	Strong negative
fut_veh_car	Strong negative
fut_veh_moto	Strong negative
own_car	Strong positive

2.3.2. Marginal effects (Slopes – slope to the mean)

```
Model 4: Logit, using observations 1-19807
Dependent variable: opinion_ban_code
Standard errors based on Hessian

                 coefficient   std. error      z         slope
  -----------------------------------------------------------------
  const          -0.765690    0.167921      -4.560
  freqpweek      -0.0468737   0.00465762   -10.06     -0.00933130
  freq_car        0.299822    0.00779928    38.44      0.0596865
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  own_car         0.748505    0.0363801     20.57      0.149007
  own_motob      -0.129485    0.0211477     -6.123    -0.0257769
  own_bike        0.349349    0.0268376     13.02      0.0695460
  own_ebike      -0.356984    0.0340136    -10.50     -0.0710660
  aware_ban_no    0.787260    0.0653841     12.04      0.136861
  aware_ban_yes   1.88110     0.0533563     35.26      0.399539
  vehic_bus      -0.402924    0.166126      -2.425    -0.0867486
  vehic_car       0.206983    0.112174       1.845     0.0403456
  vehic_ebike     0.00804117  0.122861       0.06545   0.00159820
  vehic_moto     -0.419274    0.103220      -4.062    -0.0822473
  vehic_taxi     -0.0424605   0.181870      -0.2335   -0.00853132
  vehic_tram     -0.417036    0.917422      -0.4546   -0.0902017
  vehic_walk     -0.115971    0.152545      -0.7602   -0.0236579
  fut_veh_car    -0.429139    0.131402      -3.266    -0.0878596
  fut_veh_ebike   0.238478    0.152196       1.567     0.0450928
  fut_veh_moto   -0.360590    0.133018      -2.711    -0.0752569
  fut_veh_no     -0.661277    0.130227      -5.078    -0.135262

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Likelihood ratio test: Chi-square(20) = 7925.02 [0.0000]

           Predicted
              0       1
  Actual 0   5466    2021
         1   2273   10047

Excluding the constant, p-value was highest for variable 13 (vehic_ebike)
```

Figure 11: Marginal Effects table

Variables with p - value < 0.05 are considered statistically significant predictors and presented:

Variable	Slope	Interpretation
freqpweek	−0.00933	Decrease the probability of supporting the ban by 0.93 percentage points.
freq_car	0.05969	Increase the probability by 5.97 percentage points.
own_car	0.14901	Increase the probability by 14.9 percentage points.
own_motob	−0.02578	Decrease the probability by 2.58 percentage points.
own_bike	0.06955	Increase the probability by 6.95 percentage points.
own_ebike	−0.07107	Decrease the probability by 7.11 percentage points.
aware_ban_no	0.13686	Increase the probability by 13.7 percentage points.
aware_ban_yes	0.39954	Increase the probability by 39.95 percentage points (very strong effect).
vehic_bus	−0.08675	Decrease the probability by 8.68 percentage points.
vehic_moto	−0.08225	Decrease the probability by 8.23 percentage points.
fut_veh_car	−0.08786	Decrease the probability by 8.79 percentage points.
fut_veh_moto	−0.07526	Decrease the probability by 7.53 percentage points.
fut_veh_no	−0.13526	Decrease the probability by 13.53 percentage points.
freqpweek	−0.00933	Decrease the probability of supporting the ban by 0.93 percentage points.

2.3.3. Confusion matrix

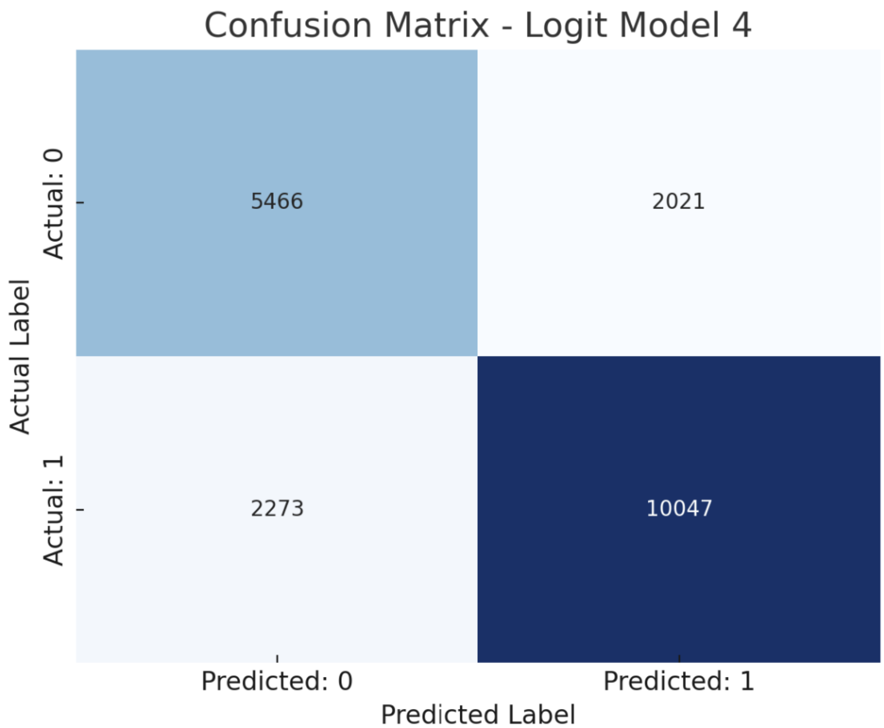

Figure 12: Confusion matrix

True positive (TP = 10,047): Cases where the person actually support the ban, and the model correctly predicts support.

True negative (TN = 5,466): Cases where the person actually opposes the ban, and the model correctly predicts opposition.

False positive (FP = 2,021): Cases where the person actually opposes the ban, but the model incorrectly predicts support.

False negative (FN = 2,273): Cases where the person actually supports the ban, but the model incorrectly predicts opposition.

The model performs reasonably well, with an accuracy 78.3%.

2.3.4. Evaluation

Strong resistance from future motorbike and car users

Individuals who plan to use motorbikes or cars in the future are significantly less supportive of the ban. This likely reflects a perceived loss of mobility freedom and inadequate alternatives.

Awareness power:

Both groups who are aware of the ban – whether supportive or not – show significantly higher support than those unaware. This suggests that transparent information campains can positively influence public opinion.

Transport mode and ownership effects:

People who walk, own bicycles, or primarily use cars show more support for the ban. In constrast, current of future motobike users are less supportive, highlighting the need to target interventions at the most impacted groups.

Public transport:

Variables related to public transport are statistically insignificant. This may reflect dissatifaction with service quality, indicating that public transit improvements are essential.

2.3.5. Recommendations

To enhance the effectiveness and public acceptability of a motorbike ban, the following recommendations are:

Supporting modal shift for motorbike users such as providing incentives (subsidies) for switching from motorbikes to e-bikes or public transport or implementing pilot programs offering free/discounted mobility passes.

Investing in public awareness by lauching information campaigns to explain the rationale, timeline, and benefits of the ban.

Improving transport alternatives by upgrading public transport infrastructure and expanding infrastructure for cycling and walking.

Phased implementation, starting with central districts, followed by gradual expansion, allowing transition periods with incentives to ease adaptation.

CONCLUSION

This study provides a multifaceted view of how personal mobility patterns, vehicle ownership, and public awareness influence attitudes toward vehicle bans in Hanoi. As a city undergoing rapid urbanization, Hanoi embodies the tension between modern transportation ambitions and the socio-economic complexities of a diverse urban population.

The analysis reveals that individuals who frequently rely on motorcycles and e-bikes—especially those who foresee using them in the future—are significantly less likely to support vehicle ban policies. Conversely, car users and those intending to rely on private cars show greater support for such regulations. This indicates that personal stake in future mobility plays a crucial role in shaping attitudes, possibly reflecting deeper issues of class, accessibility, and transport equity.

Furthermore, the strong positive influence of policy awareness on support for the ban highlights a critical policy lever: knowledge and communication. Citizens who are informed about the ban are significantly more likely to support it, suggesting that public awareness campaigns could play a transformative role in shifting public opinion and ensuring policy acceptance.

To build on these findings, several directions for future research are recommended:

> **Qualitative Insights**: Incorporate in-depth interviews or focus groups to understand the emotional, cultural, and practical reasons behind resistance or support for mobility restrictions.
>
> **Spatial and Geographic Analysis**: Explore how attitudes vary across districts or peri-urban zones of Hanoi, especially where public transport is less accessible.
>
> **Policy Simulation Studies**: Use behavioral experiments or discrete choice modeling to forecast how different groups would respond to alternative mobility policies (e.g., subsidies for e-scooters, improved bus routes).

In sum, this study contributes to a deeper understanding of urban transportation governance in the Global South. As Hanoi positions itself as a greener, more livable city, its policies must align not only with global environmental goals but also with the lived realities of its citizens.

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