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.

The model along with other exploratory analysyes were presented in project using Jupyter Notebook – an open source scientific computing platform developed in Python, R, and Julia.

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.

1.4. Overview of selected dataset

The dataset provided by Open Science Framework is collected for the purpose of assessing social behavior in transportation mode choice. To reduce complexity, the core important variables are selected as follows:

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.

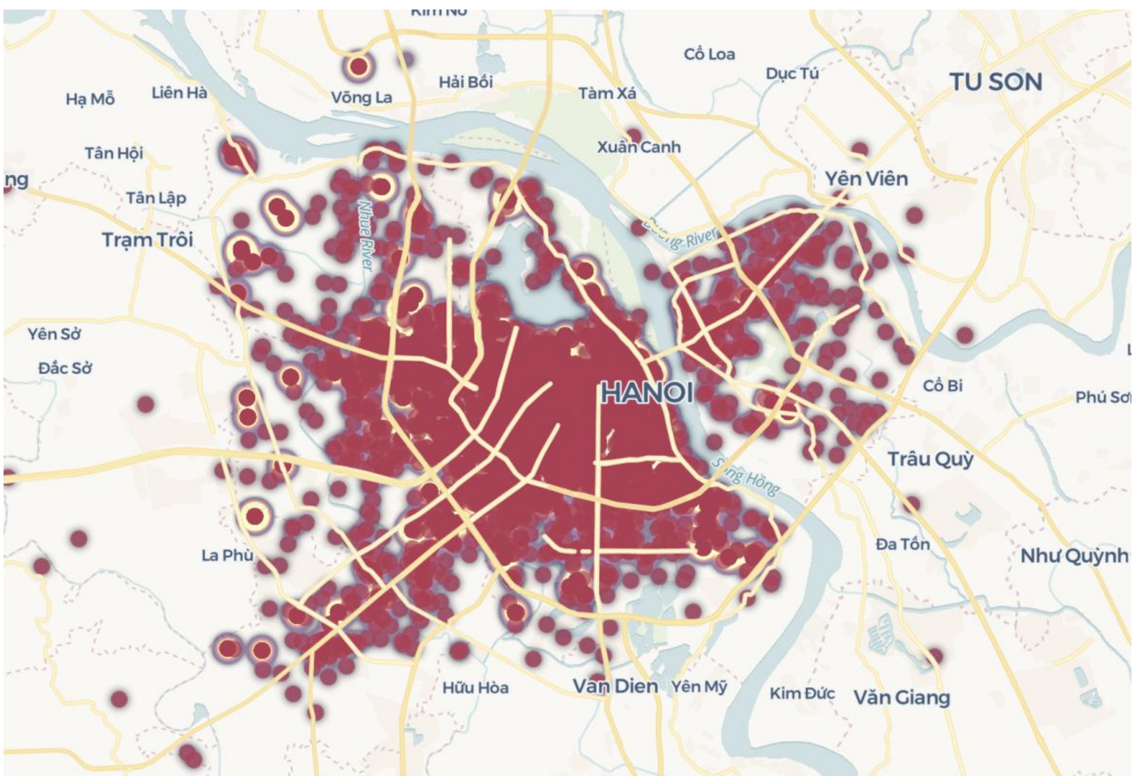

Figure 2: Traffic density map in central districts of Hanoi

CHAPTER 2: DATA ANALYSIS

2.1. Data Visualization

2.1.1. People opinion on travel modes

- At the vehicle ownership:

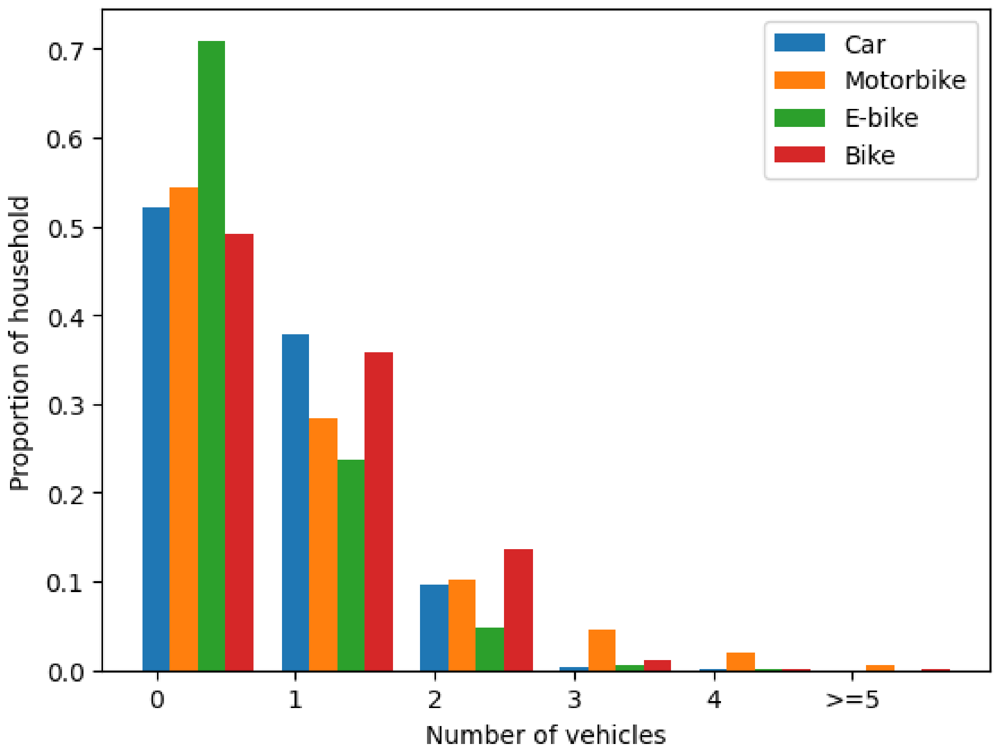

Figure 3: Vehicle ownership / Household

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:

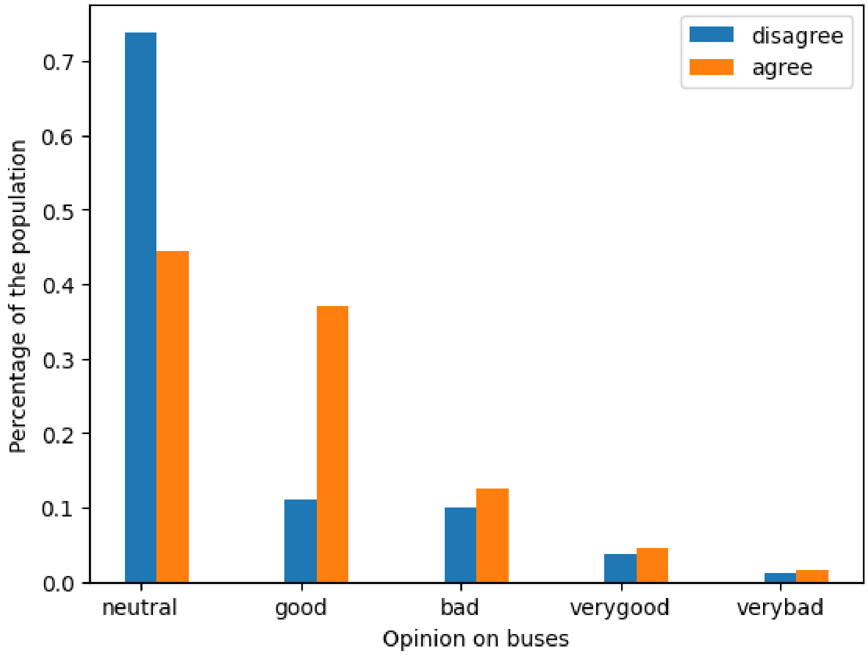

Figure 4: Bus opinion distribution by ban attitude

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:

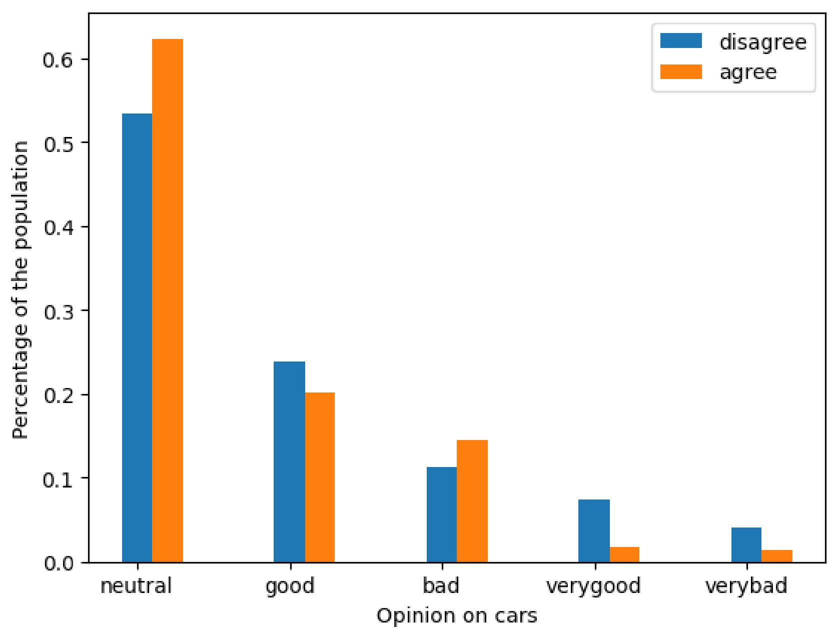

Figure 5: Car opinion distribution by ban attitude

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:

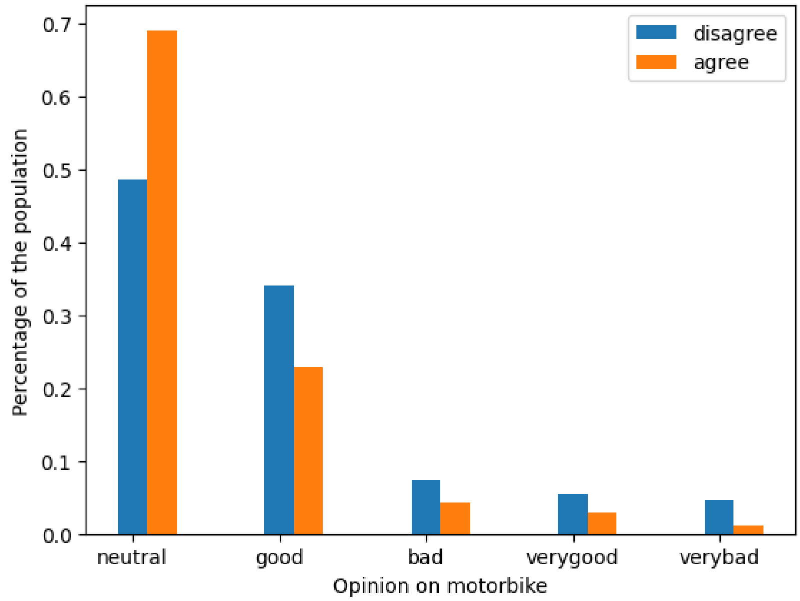

Figure 6: Motobike opinion distribution by ban attitude

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

2.1.2. Descriptive analysis

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

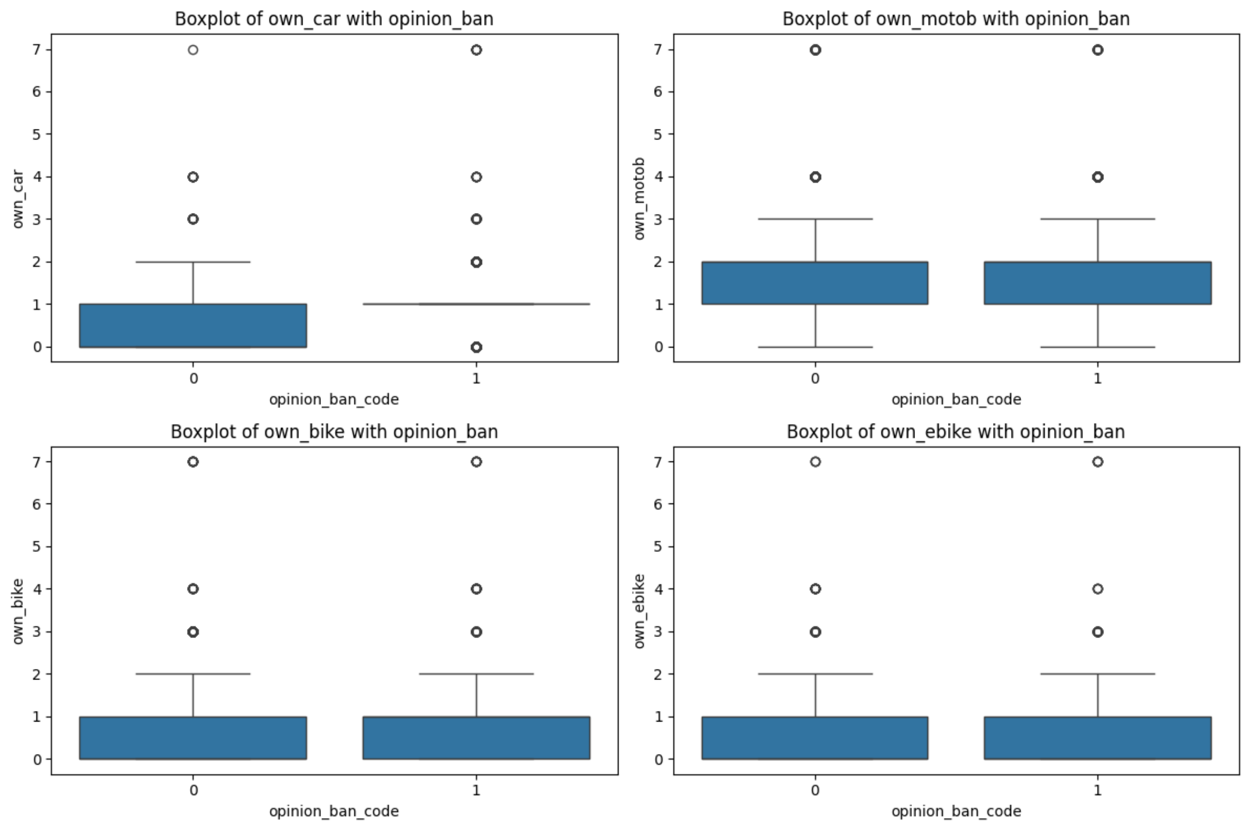

Figure 7: Boxplot of four variables with opinion_ban

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. ($r\neq0$)

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 test

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.

No.	Variable	VIF
1	vehic_moto	**9.083**
2	fut_veh_no	6.509
3	fut_veh_car	6.174
4	own_motob	5.750
5	vehic_car	4.851
6	aware_ban_yes	4.412
7	fut_veh_moto	4.289
8	freqpweek	3.978
9	own_car	3.256
10	own_bike	1.998
11	aware_ban_no	1.991
12	freq_car	1.845
13	vehic_ebike	1.772
14	fut_veh_ebike	1.746
15	own_ebike	1.581
16	vehic_walk	1.307
17	vehic_bus	1.220
18	vehic_taxi	1.149
19	vehic_tram	1.008
20	dist_to_pub	1.001

Figure 8: VIF Table

Generally, no variable has a VIF > 10, so there's no servere multicollinearity. However, **vehic_moto** variable will be erased because VIF is 9.083. Besides, some variables have VIF > 5, indicating moderate to high multicollinearity, which might affect the stability of regression coefficients.

2.3. Developing a regression model

2.3.1. Binary Logistic Regression

Binary logistic regression is similar in principle to linear regression – it models an outcome as a function of one or more predictors. The main distinction, however, is the form of the outcome. In linear regression, the outcome is a continuous variable, taking on values over a range of possible values. In binary logistic regression, the outcome is binary: a categorical variable with exactly two possible values.

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

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).

2.3.2. Results table

```
                           Logit Regression Results
==============================================================================
Dep. Variable:      opinion_ban_code   No. Observations:                19807
Model:                         Logit   Df Residuals:                    19788
Method:                          MLE   Df Model:                           18
Date:               Fri, 16 May 2025   Pseudo R-squ.:                  0.2987
Time:                       19:51:18   Log-Likelihood:                -9211.1
converged:                      True   LL-Null:                       -13134.
Covariance Type:           nonrobust   LLR p-value:                     0.000
=================================================================================
```

Figure 9: Model Overview

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

Number of observations: 19,807.

Pseudo R-squared (McFadden's R – squared) is 0.2987 => Reasonable explanatory power for social science data.

Log-Likelihood Ratio (LLR) p – value: 0.000 => The model overall is statistically significant.

```
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
freqpweek     -0.0556      0.005    -12.176      0.000      -0.065      -0.047
freq_car       0.2961      0.008     38.723      0.000       0.281       0.311
dist_to_pub -4.618e-05    2.4e-05    -1.923      0.055   -9.33e-05    8.94e-07
own_car        0.7174      0.036     19.888      0.000       0.647       0.788
own_motob     -0.1584      0.021     -7.541      0.000      -0.200      -0.117
own_bike       0.3467      0.027     13.067      0.000       0.295       0.399
own_ebike     -0.3552      0.034    -10.483      0.000      -0.422      -0.289
aware_ban_no   0.6905      0.063     10.894      0.000       0.566       0.815
aware_ban_yes  1.7920      0.052     34.627      0.000       1.691       1.893
vehic_bus     -0.0611      0.135     -0.452      0.652      -0.326       0.204
vehic_car      0.5548      0.054     10.355      0.000       0.450       0.660
vehic_ebike    0.3451      0.077      4.456      0.000       0.193       0.497
vehic_taxi     0.1870      0.155      1.203      0.229      -0.118       0.492
vehic_tram     0.0184      0.909      0.020      0.984      -1.763       1.799
vehic_walk     0.2458      0.118      2.078      0.038       0.014       0.478
fut_veh_car   -1.3535      0.075    -17.989      0.000      -1.501      -1.206
fut_veh_ebike -0.6171      0.110     -5.589      0.000      -0.834      -0.401
fut_veh_moto  -1.2724      0.078    -16.262      0.000      -1.426      -1.119
fut_veh_no    -1.5984      0.068    -23.345      0.000      -1.733      -1.464
==============================================================================
```

Figure 10: Regression coefficients outcome

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

Variable	Coef	Odds Ratio	Interpretation
freqpweek	-0.056	0.946	Each additional trip per week reduces the odds of supporting the ban by 5.4%.
freq_car	0.296	1.345	Each unit increase in car use raises the odds of support by 34.5%.
own_car	0.717	2.049	Car owners are about 2.05 times more likely to support the ban.
own_motob	-0.158	0.854	Motorbike owners have 14.6% lower odds of supporting the ban.

own_bike	0.347	1.415	Bike owners have 41.5% higher odds of supporting the ban.
own_ebike	-0.355	0.701	E-bike owners are 29.9% less likely to support the ban.
aware_ban_no	0.691	1.996	Those aware but said “no” are nearly 2 times more likely to support.
aware_ban_yes	1.792	6.001	Respondents already aware and answering “yes” are 6 times more likely to support.
vehic_car	0.555	1.742	Car users (main transport) are 74.2% more likely to support the ban.
vehic_ebike	0.345	1.412	E-bike users (main transport) are 41.2% more likely to support the ban.
vehic_walk	0.246	1.279	Walking as main mode increases odds by 27.9%.
fut_veh_car	-1.354	0.258	Future car users are 74.2% less likely to support the ban.
fut_veh_ebike	-0.617	0.540	Future e-bike users are 46.0% less likely to support.
fut_veh_moto	-1.272	0.280	Future motorbike users are 72.0% less likely to support.
fut_veh_no	-1.598	0.202	Those not planning any future vehicle use are 79.8% less likely to support the ban.

From the above results tables, the top variables with the largest impact:

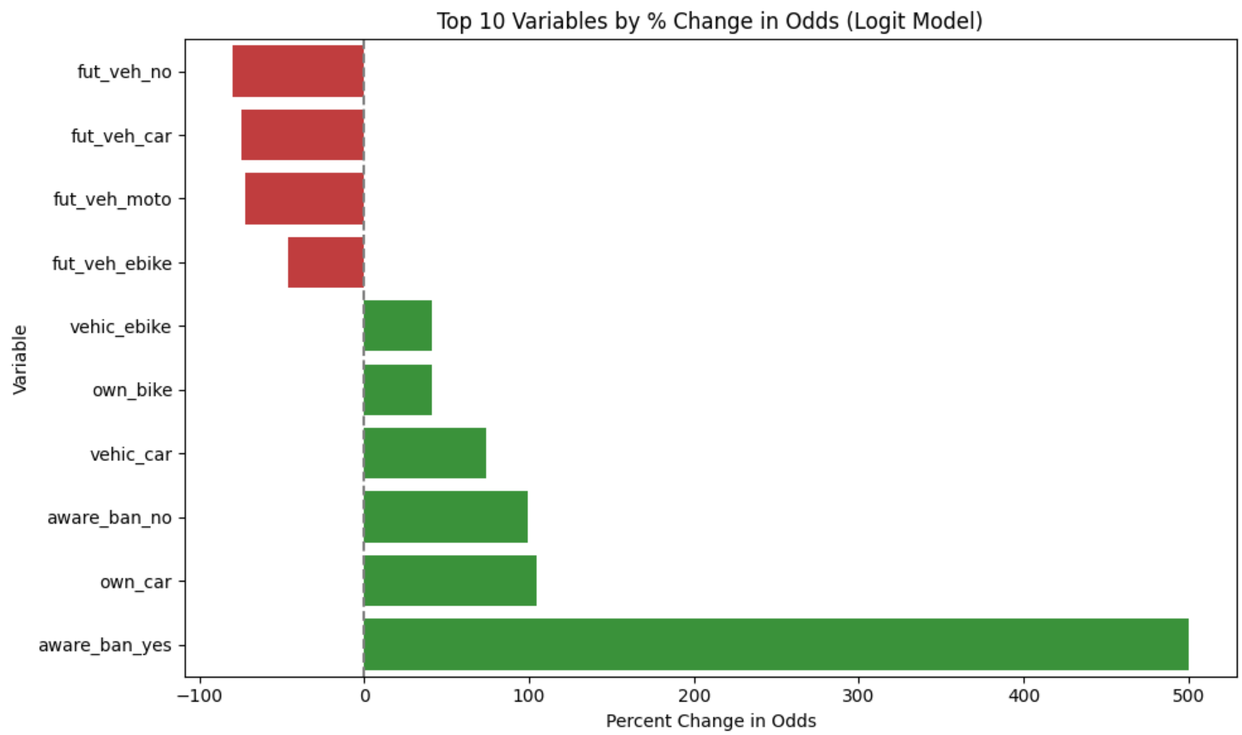

Figure 11: Top 10 variables with the largest impact

To be more specific:

Variable	Coef	Odds Ratio	Impact
aware_ban_yes	1.792	6.001	Very strong positive
fut_veh_no	−1.598	0.202	Strong negative
fut_veh_car	−1.354	0.258	Strong negative
fut_veh_moto	−1.272	0.280	Strong negative
own_car	0.717	2.049	Strong positive

2.3.3. *Marginal effects (Slopes – slope to the mean)*

```
        Logit Marginal Effects
=====================================
Dep. Variable:       opinion_ban_code
Method:                          dydx
At:                           overall
================================================================================
                  dy/dx    std err          z      P>|z|      [0.025      0.975]
--------------------------------------------------------------------------------
freqpweek       -0.0086      0.001    -12.362      0.000      -0.010      -0.007
freq_car         0.0457      0.001     44.280      0.000       0.044       0.048
dist_to_pub  -7.134e-06   3.71e-06     -1.924      0.054   -1.44e-05    1.35e-07
own_car          0.1108      0.005     20.777      0.000       0.100       0.121
own_motob       -0.0245      0.003     -7.580      0.000      -0.031      -0.018
own_bike         0.0536      0.004     13.289      0.000       0.046       0.061
own_ebike       -0.0549      0.005    -10.603      0.000      -0.065      -0.045
aware_ban_no     0.1067      0.010     11.011      0.000       0.088       0.126
aware_ban_yes    0.2768      0.007     39.430      0.000       0.263       0.291
vehic_bus       -0.0094      0.021     -0.452      0.651      -0.050       0.032
vehic_car        0.0857      0.008     10.446      0.000       0.070       0.102
vehic_ebike      0.0533      0.012      4.466      0.000       0.030       0.077
vehic_taxi       0.0289      0.024      1.203      0.229      -0.018       0.076
vehic_tram       0.0028      0.140      0.020      0.984      -0.272       0.278
vehic_walk       0.0380      0.018      2.079      0.038       0.002       0.074
fut_veh_car     -0.2091      0.011    -18.550      0.000      -0.231      -0.187
fut_veh_ebike   -0.0953      0.017     -5.604      0.000      -0.129      -0.062
fut_veh_moto    -0.1966      0.012    -16.681      0.000      -0.220      -0.173
fut_veh_no      -0.2469      0.010    -24.691      0.000      -0.267      -0.227
================================================================================
```

Figure 12: Marginal Effects table

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

Variable	ME (dy/dx)	Interpretation (1 unit increase)
freqpweek	-0.0086	A 1-unit increase in public transport frequency per week decreases support for the ban by 0.86 percentage points.
freq_car	0.0457	A 1-unit increase in car use frequency increases support for the ban by 4.57 percentage points.

own_car	0.1108	Owning a car increases support for the ban by 11.08 percentage points.
own_motob	-0.0245	Owning a motorbike decreases support for the ban by 2.45 percentage points.
own_bike	0.0536	Owning a bike increases support for the ban by 5.36 percentage points.
own_ebike	-0.0549	Owning an e-bike decreases support for the ban by 5.49 percentage points.
aware_ban_no	0.1067	Being aware of the ban (but not supportive) increases support by 10.67 percentage points compared to the reference group.
aware_ban_yes	0.2768	Being aware and supportive of the ban increases support by 27.68 percentage points.
vehic_car	0.0857	Primarily using a car increases support by 8.57 percentage points compared to the reference group.
vehic_ebike	0.0533	Primarily using an e-bike increases support by 5.33 percentage points.
vehic_walk	0.0380	Primarily walking increases support by 3.8 percentage points.
fut_veh_car	-0.2091	Intending to use a car in the future decreases support by 20.91 percentage points.
fut_veh_ebike	-0.0953	Intending to use an e-bike in the future decreases support by 9.53 percentage points.
fut_veh_moto	-0.1966	Intending to use a motorbike in the future decreases support by 19.66 percentage points.

fut_veh_no	-0.2469	Having no intention to use any vehicle in the future decreases support by 24.69 percentage points.

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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