Estimating Causal Effects of Restaurant Supply on UberEats Orders*

MSIN0309 Case Study

Dr. Wei Miao

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1 Industry Background

The food delivery industry has witnessed explosive growth, transforming how urban consumers dine. Platforms like UberEats serve as two-sided marketplaces connecting hungry customers with a variety of local restaurants. A critical driver of platform growth is the **cross network effect**: a wider selection of restaurants attracts more customers, which in turn generates more orders.

For UberEats, understanding the precise causal effect of restaurant density (supply) on total orders (demand) is vital for strategic decision-making. If increasing the number of restaurants significantly boosts total orders (rather than just cannibalising existing ones), the platform should invest heavily in onboarding new merchants.

In this case study, we examine the causal link between the **number of restaurants** and **total orders** in London postcodes. We will tackle the endogeneity challenges inherent in this economic relationship using Instrumental Variables (IV).

2 Data Description

We focus on a cross-sectional dataset covering London postcodes (e.g., E1, W1, WC1) in Week 1 of 2024. The data science team has aggregated transaction logs into a postcode-level dataset.

The dataset `data_london` contains the following key variables:

- `postcode_area`: The London postcode district (e.g., "E1").
- `n_restaurants`: Number of active restaurants on the platform.
- `total_orders`: Aggregated number of orders in the week.
- `hygiene_inspections`: Number of random hygiene inspections conducted by local council authorities.
- `avg_income`: Average annual income in the postcode (in thousands GBP).
- `year`: Year of observation (2024).
- `week`: Week of observation (Week 1).

*This case was prepared by Wei Miao, UCL School of Management. This case was developed to provide material for class discussion rather than to illustrate either effective or ineffective handling of a business situation. Names and data may have been disguised or fabricated.

3 Empirical Analysis

We wish to estimate the regression:

$$TotalOrders_i = \beta_0 + \beta_1 Restaurants_i + \gamma Control_i + \varepsilon_i$$

3.1 Endogeneity and OLS

Question 1

1. Run a simple OLS regression of `total_orders` on `n_restaurants`, controlling for `avg_income`.
2. Discuss the endogeneity problem. Specifically, explain how **Omitted Variable Bias (OVB)**, **Reverse Causality**, and **Measurement Error** might bias your estimate of β_1.

3.2 Instrumental Variables (IV)

To solve the endogeneity problem, we propose using **Hygiene Inspections** (`hygiene_inspections`) as an instrument for `n_restaurants`. These are random audits conducted by local authorities to ensure food safety compliance. In our setting, we treat these inspections as randomly assigned or policy-driven shocks that are unrelated to the current consumer demand (unconfoundedness).

Question 2

1. Argue whether `hygiene_inspections` satisfies the **Relevance** and **Exclusion** conditions.
2. Perform a Two-Stage Least Squares (2SLS) regression, controlling for `avg_income`. Report the first stage and second stage results. Interpret the causal effect.

4 Managerial Implications

Question 3
Using a back-of-the-envelope calculation, illustrate the financial consequence of using the biased OLS estimate versus the causal IV estimate.
Assume the following:

- UberEats is considering a marketing campaign to onboard **10 new restaurants** in a specific postcode.
- The cost of this campaign is **£2,000**.
- UberEats makes a margin of **£5 per order**.
- Use the coefficients from your OLS and 2SLS regressions above.

Should UberEats proceed with the campaign?

5 Intent-to-Treat (ITT) and Encouragement Design

In some contexts, instrumental variables are used to analyse randomised experiments where compliance is imperfect. This is often called an **Encouragement Design**.

For example, suppose UberEats ran an experiment where they randomly offered subsidies to potential restaurant partners in certain postcodes (Treatment) but not others (Control).

- **Instrument (Z)**: The random assignment to the subsidy offer (Intent-to-Treat).
- **Endogenous Treatment (X)**: Whether the restaurant actually joined the platform.
- **Outcome (Y)**: Total orders.

Even if we cannot force restaurants to join, the random assignment (Z) is a perfect instrument for participation (X) because it is random (exogenous) and strongly influences participation (relevant). The IV estimate then recovers the **Local Average Treatment Effect (LATE)**: the effect of joining the platform for those restaurants who were induced to join *because* of the subsidy.

In our current case, we can view the random hygiene inspections similarly: they are an exogenous "discouragement" (negative instrument) randomly assigned by the government, which shifts the supply curve of restaurants, allowing us to trace out the demand curve.