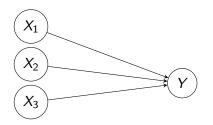
Oral presentation 3 - Econometric Results

DEVYNCK Tom, DRUILHE Théo, FOUQUET Damien

March 1, 2024

Research question

Are credit allocation model discriminating? The american experience



Where:

- X_1 is the race of the applicant
- X_2 is he sex of the applicant
- X_3 is the two applicants have the same sex
- Y is the probability of the credit being denied

Main econometric specification

We consider the following logistic model:

$$(\mathcal{LM})$$
 : $\mathbb{P}(\textit{deny}_i = 1) = rac{1}{1 + \mathrm{e}^{X_i'eta}}$

where:

- deny_i is a dummy variable that equals one if the credit of applicant i is denied, 0 otherwise.
- $X_i'\beta$ is a linear combination of variables of interest

We now want to choose relevant variables to represent the utility function of the bank $U_i = X_i' \beta$.

First (naive) model

Naively, since we want to evaluate the impact of our discriminatory variables on the probability of having its application denied, we choose :

$$U_i = \beta_0 + \beta_1 sex_i + \beta_2 race_i + \beta_3 same_sex_i + \varepsilon_i$$

Plugging it in (\mathcal{LM}) , we denote our first model $(\mathcal{LM}1)$.

We estimate ($\mathcal{LM}1$) with the Maximum Likelihood (ML) method and find the following estimates:

First model - Results

Coefficient	Estimate	p-value
(Intercept)	-1.68	< 2e-16 ***
Asian	0.09	0.002 **
Black	0.904201	< 2e-16 ***
Native	0.75	< 2e-16 ***
Women	0.028	0.012 *
Same Sex	-0.12	0.004 **

Table: Model 1 - Results

Second model - Motivation

It is obvious that there is endogeneity in this model so that we need to add control variables (since they are contained in the error term and influences *deny*; through it).

We now choose:

$$\begin{aligned} U_i &= \left[\beta_0 + \beta_1 \mathsf{race}_i + \beta_2 \mathsf{sex}_i + \beta_3 \mathsf{same_sex}_i\right] + \left[\beta_4 \mathsf{age}_i + \beta_5 \mathsf{purpose}_i \right. \\ &+ \beta_6 \mathsf{amount}_i + \beta_7 \mathsf{income}_i + \beta_8 \mathsf{property_value}_i + \beta_9 \mathsf{loan_term}_i\right] + \varepsilon_i \end{aligned}$$

and plugging it in (\mathcal{LM}) , we denote our second model $(\mathcal{LM}2)$.

We estimate ($\mathcal{LM}2$) with the ML method and find the following estimates.

Second model - Results & Interpretation

Variable	Estimate	p-value
(Intercept)	-2.532	< 2e-16 ***
Asian	0.44	< 2e-16 ***
Black	0.826	< 2e-16 ***
Native	0.604	< 2e-16 ***
Women	-0.05	1.88e-05 ***
Same Sex	2.849e-01	2.00e-11 ***
Age <25	-0.068	0.0542
Age >74	-0.114	6.95e-05 ***
Age 25-34	-0.132	8.15e-13 ***
Age 45-54	2.506e-05	0.9988
Age 55-64	-0.121	1.42e-11 ***
Age 65-74	-0.20	< 2e-16 ***
Home improvement	1.742	< 2e-16 ***
Other purpose	1.879	< 2e-16 ***
Refinancing	1.090	< 2e-16 ***
Cash-out refinancing	1.094	< 2e-16 ***
Loan amount	-6.591e-09	< 2e-16 ***
Income	-6.493e-06	< 2e-16 ***
Property_value	-8.369e-07	< 2e-16 ***
Loan term	2.279e-03	< 2e-16 ***

Table: Logistic Regression Results

Second model - Results & Interpretation (2)

Coefficients of logistic models cannot be interpreted directly.

We decided to create an "average" candidate, defined as follows:

- Mean value for numerical variables
- Mode: most common value for categorical variables

Second model - Results & Interpretation (3)

 $ar{X} = \left(ar{x_1}, ar{x_2}, ..., ar{x_6}
ight)$ value of the "average" candidate defined previously

Probability of deny	Value
$P(deny race = black, X = \bar{X})$	0.14
$P(deny race = native, X = \bar{X})$	0.115
$P(deny race = asian, X = \bar{X})$	0.10
$P(deny race = white, X = \bar{X})$	0.066

Interpretation:

A black person is more than **2 times more likely** to have his credit rejected, just because he is black.

Second model - Results & Interpretation (4)

Cross-effect of race and sex:

Probability of deny	Value
$P(deny race = black, sex = men, X = \bar{X})$	0.14
$P(deny race = black, sex = women, X = \bar{X})$	0.133
$P(deny race = white, sex = men, X = \bar{X})$	0.066
$P(deny race = white, sex = women, X = \bar{X})$	0.063

Interpretation:

There is **not** a **great effect** of sex, but women always have a slightly lower probability of deny.