Regression analysis when there is random assignment

- We can write the observed outcome as:

$$Y_i = Y_i(0)\,(1 - D_i) + Y_i(1)\,D_i$$

$$\Rightarrow Y_i = \underbrace{\alpha}_{E(Y_i(0))} + \underbrace{\tau}_{[E(Y_i(1)) - E(Y_i(0))]} D_i + \underbrace{\eta_i}_{Disturbance}$$

- τ :Treatment effect!
- Let's add covariates: $Y_i = \alpha + \tau D_i + \gamma X_i + \eta_i$
  - If there is D_i randomly assigned (there is no selection bias), X_is should not be related with treatment $\Rightarrow$ they will not affect the estimate of τ
  - But they may explain $Y_i \Rightarrow$ It lowers the s.e. of the regression estimates (we will see an example)

Regression analysis when there is random assignment

- When covariates (strongly) predict the outcome, precision improves
  - If possible, it would be important to collect additional relevant information (e.g. through a survey)
  - You can show this using (you can replace Y_i by $Y_i - X_i$):

$$SE(\widehat{ATE}) = \sqrt{\frac{Var(Y_i(0)) + Var(Y_i(1)) + 2Cov(Y_i(0), Y_i(1))}{N-1}}$$

- As we have discussed, there is a problem when covariates are added at discretion depending on the result
  - Plan in advance what covariates should be included
  - Present changes in results to judge whether adding covariates is consequential

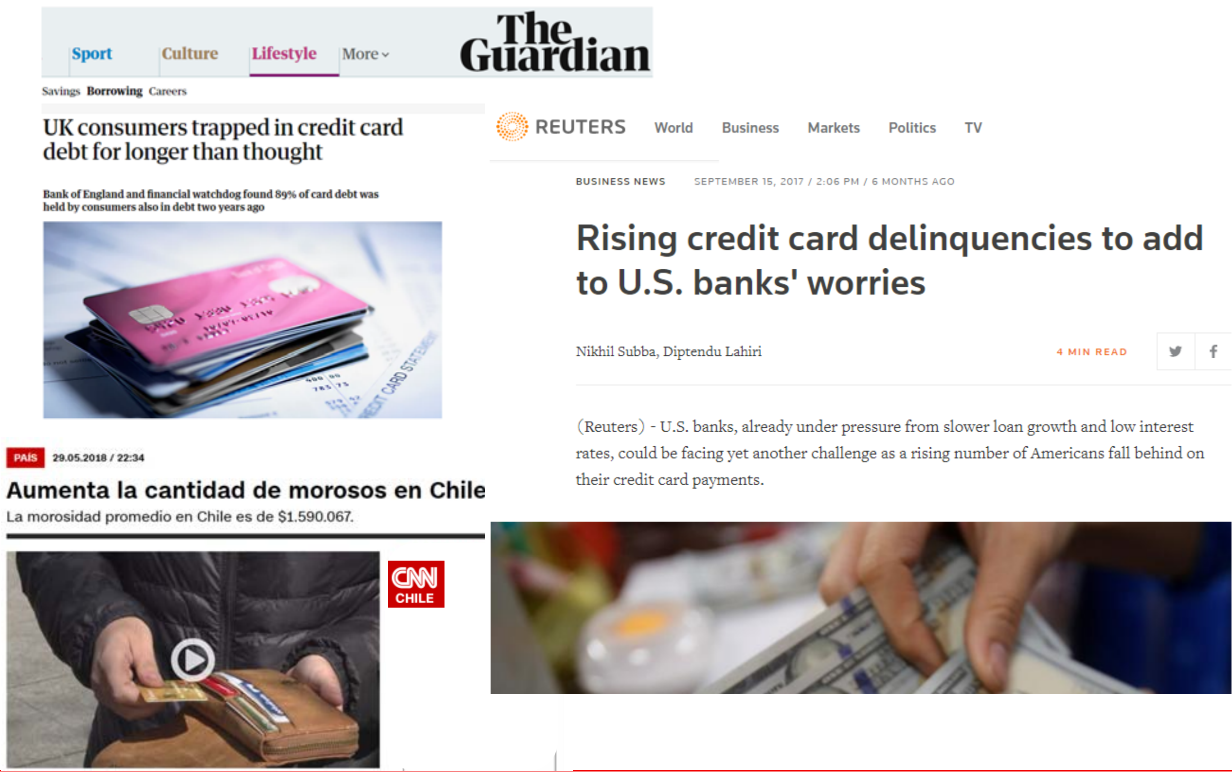
Heterogeneous treatment effects

- Imagine you are testing whether sales improve when you add a gift to a product. You may wonder whether the effect depends on the person (e.g. age)
  - τ varies
- This means interactions allow us to know when the treatment may be more effective

$$Y_i = \alpha + \tau D_i + \gamma X_i + \rho D_i X_i + \eta_i$$

- This way of examining group variations (e.g. by gender) is non-experimental
  - One may include another treatment (e.g. 2 × 2 factorial design)

Aplication


Sport Culture Lifestyle More

The Guardian

Savings Borrowing Careers

UK consumers trapped in credit card debt for longer than thought

Bank of England and financial watchdog found 89% of card debt was held by consumers also in debt two years ago

PAÍS 29.05.2018 / 22:34

Aumenta la cantidad de morosos en Chile

La morosidad promedio en Chile es de $1.590.067.

CNN CHILE

REUTERS World Business Markets Politics TV

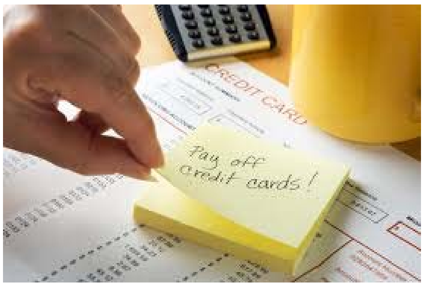
BUSINESS NEWS SEPTEMBER 15, 2017 / 2:06 PM / 6 MONTHS AGO

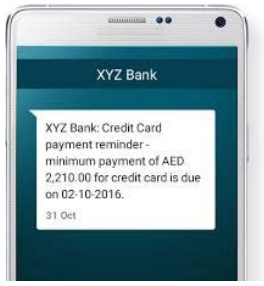
Rising credit card delinquencies to add to U.S. banks' worries

Nikhil Subba, Diptendu Lahiri 4 MIN READ

(Reuters) - U.S. banks, already under pressure from slower loan growth and low interest rates, could be facing yet another challenge as a rising number of Americans fall behind on their credit card payments.

What if we “only” remind people to pay…





- Increase adherence to health treatments (Altmann and Traxler 2014)
- Increase personal savings (Karlan et al. 2016)
- Can it help in this case?

Many interesting results (1)

	Control	Treatment	p (after F-test)
Male	48.41%	48.42%	0.984
	0.24%	0.14%	
Age	44.319	44.391	0.323
	0.063	0.037	
Total balance (norm)	0.005	0.002	0.618
	0.005	0.003	
Credit lines (norm)	0.000	0.000	0.998
	0.005	0.003	
Card tenure	135.341	135.173	0.780
	0.521	0.301	
Children	1.494	1.494	0.950
	0.006	0.004	
Vehicles	0.974	0.976	0.832
	0.006	0.004	
Problems before to pay	0.056	0.056	0.921
	0.001	0.001	
N	44932	134818	

- What do you conclude?

Many interesting results (2)

	(1) ln_payment	(2) ln_payment
treat	0.0552**	0.0538**
	(0.0186)	(0.0175)
male		-0.0525***
		(0.0156)
age		-0.0031***
		(0.0008)
total_billed_norm		0.3676***
		(0.0113)
credit_line_norm		-0.1264***
		(0.0115)
tenure_card		-0.0015***
		(0.0001)
nchildren		-0.0175*
		(0.0070)
vehicles		-0.0536***
		(0.0057)
Constant	11.0808***	11.5277***
	(0.0161)	(0.0326)
Additional controls	No	Yes
r2	0.0001	0.1117
N	179753	179751

+ p<0.10, * p<0.05, ** p<0.01, *** p<0.001

- Write down the model
- What do you conclude?
- Did you the R^2?

Many interesting results: What do we learn here? (3)

	(1) ln_payment	(2) ln_payment	(3) ln_payment
treat=1	0.0632**	-0.0480	0.0427*
	(0.0244)	(0.0604)	(0.0180)
treat=1 # male	-0.0192		
	(0.0350)		
treat=1 # age		0.0023+	
		(0.0013)	
treat=1 # did_not_pay			0.2004**
			(0.0763)
Male	-0.0387	-0.0530***	-0.0531***
	(0.0305)	(0.0156)	(0.0156)
age	-0.0029***	-0.0046***	-0.0029***
	(0.0008)	(0.0013)	(0.0008)
did_not_pay	-0.7933***	-0.7933***	-0.9460***
	(0.0333)	(0.0333)	(0.0662)
Constant	11.5377***	11.6210***	11.5532***
	(0.0349)	(0.0542)	(0.0327)
Additional controls	Yes	Yes	Yes
r2	0.1145	0.1145	0.1146
N	179751	179751	179751

+ p<0.10, * p<0.05, ** p<0.01, *** p<0.001