Estimation of the Rebound Effect for Travel Distance Using Micro-level Data for France

Catherine Benjamin
catherine.benjamin@univ-rennes1.fr

Alejandra Giraldo
deici.giraldo@univ-rennes1.fr

Quatrième Conférence Évaluation des politiques publiques - AFSE
Paris - 13 December 2018

How to cut driving emissions?

- The share of global energy-related GHG emissions due to transportation is 23% (EEA, 2017).

- In France, it is 28,5% of which 53,7% are due to private vehicles (Pourquier and Vicard, 2017).

How to cut driving emissions?

- The share of global energy-related GHG emissions due to transportation is 23% (EEA, 2017).
- In France, it is 28,5% of which 53,7% are due to private vehicles (Pourquier and Vicard, 2017).
- Efficiency policies are widely used as a way to reduce greenhouse gas emissions.
- More efficiency usually means a *fall in the real cost* of unit energy service, e.g. driving.
- A lower real cost of driving creates incentives to drive more.

The rebound effect

- *The increase in demand for energy services following an improvement of energy efficiency is known as the* ***rebound effect****.*

The rebound effect

- *The increase in demand for energy services following an improvement of energy efficiency is known as the **rebound effect**.*

- A **rebound effect** implies that the benefits from rising efficiency are lower than expected.

The rebound effect

- *The increase in demand for energy services following an improvement of energy efficiency is known as the* ***rebound effect****.*

- A **rebound effect** implies that the benefits from rising efficiency are lower than expected.

- Three types of rebound effect (Sorrell and Dimitropoulos, 2008):

The rebound effect

- *The increase in demand for energy services following an improvement of energy efficiency is known as the **rebound effect**.*

- A **rebound effect** implies that the benefits from rising efficiency are lower than expected.

- Three types of rebound effect (Sorrell and Dimitropoulos, 2008):
  - Direct rebound effect
  - Indirect rebound effect
  - Economy-wide rebound effect

The rebound effect

- *The increase in demand for energy services following an improvement of energy efficiency is known as the* ***rebound effect****.*

- A **rebound effect** implies that the benefits from rising efficiency are lower than expected.

- Three types of rebound effect (Sorrell and Dimitropoulos, 2008):
  - **Direct rebound effect**
  - Indirect rebound effect
  - Economy-wide rebound effect

The rebound effect

- *The increase in demand for energy services following an improvement of energy efficiency is known as the **rebound effect**.*

- A **rebound effect** implies that the benefits from rising efficiency are lower than expected.

- The **direct rebound effect** is defined as:

The rebound effect

- *The increase in demand for energy services following an improvement of energy efficiency is known as the* ***rebound effect****.*

- A **rebound effect** implies that the benefits from rising efficiency are lower than expected.

- The **direct rebound effect** is defined as:
  - The efficiency elasticity of demand for driving (VKT)

Key findings

- Most studies focus on the U.S., using panel data at a state level. Only few use micro-level data.

- Estimates range from 5% (Greene, 1992) to 40% (Linn, 2016) for the US. At the European level, they go from 9% (Stapleton et al., 2016) to 70% (Frondel and Vance, 2013).

- Some assumptions widely used in the literature can be potential sources of bias in estimations (Gillingham et al., 2016; Sorrell and Dimitropoulos, 2008).

Estimating the direct rebound effect in France

- We use the **primary definition** of the direct rebound effect: *The efficiency elasticity of demand for driving (VKT)* and account for three main sources of bias.

- We use micro-level data in France for 2008 and improve the methodology in Linn (2016) by controlling for selection bias.

- Our rich database allows us to account for household heterogeneity and vehicle characteristics, thus enhancing the rebound effect estimates.

Data

- The main data-set comes from the 2007-2008 National Transport and Travel Survey (NTTS) for France

Data

- The main data-set comes from the 2007-2008 National Transport and Travel Survey (NTTS) for France

- It gives detailed information for 20.200 households' mobility

Data

- The main data-set comes from the 2007-2008 National Transport and Travel Survey (NTTS) for France

- It gives detailed information for 20.200 households' mobility

- The dependent variable, VKT, measures the travel distance during a reference week for *one* vehicle

Data

- The main data-set comes from the 2007-2008 National Transport and Travel Survey (NTTS) for France
- It gives detailed information for 20.200 households' mobility
- The dependent variable, VKT, measures the travel distance during a reference week for *one* vehicle
- Fuel economy, E, is the inverse on-road fuel intensity per 100 km

Data

- The main data-set comes from the 2007-2008 National Transport and Travel Survey (NTTS) for France

- It gives detailed information for 20.200 households' mobility

- The dependent variable, VKT, measures the travel distance during a reference week for *one* vehicle

- Fuel economy, E, is the inverse on-road fuel intensity per 100 km

- Fuel economy is available for *one* or *two* households vehicles

Model structure

$$ln(VKT_{hi}) = \beta_0^{vkt} + \beta_1^{vkt} ln(P_f) + \beta_2^{vkt} ln(E_{hi}) + \beta_3^{vkt} ln(E_{hj}) + X_h + \epsilon_{hi}$$

Model structure

$$\overbrace{ln(VKT_{hi})}^{\boxed{\text{Distance}}} = \beta_0^{vkt} + \beta_1^{vkt} ln(P_f) + \beta_2^{vkt} ln(E_{hi}) + \beta_3^{vkt} ln(E_{hj}) + X_h + \epsilon_{hi}$$

Model structure

$$\overbrace{ln(VKT_{hi})}^{\boxed{\text{Distance}}} = \beta_0^{vkt} + \overbrace{\beta_1^{vkt} ln(P_f)}^{\boxed{\text{Fuel price}}} + \overbrace{\beta_2^{vkt} ln(E_{hi}) + \beta_3^{vkt} ln(E_{hj})}^{\boxed{\text{Fuel economy}}} + X_h + \epsilon_{hi}$$

- Separate coefficients for fuel prices and fuel economy to allow for asymmetrical responses of demand.

Model structure

$$\underbrace{ln(VKT_{hi})}_{\text{Distance}} = \beta_0^{vkt} + \underbrace{\beta_1^{vkt} ln(P_f)}_{\text{Fuel price}} + \underbrace{\beta_2^{vkt} ln(E_{hi}) + \beta_3^{vkt} ln(E_{hj})}_{\text{Fuel economy}} + X_h + \epsilon_{hi}$$

$$ln(E_{hi}) = \beta_0^{fei} + \beta_1^{fei} ln(VKT_{hi}) + \beta_2^{fei} ln(\bar{P}_f) + X_h + \epsilon_{hi}$$

$$ln(E_{hj}) = \beta_0^{fej} + \beta_1^{fej} ln(VKT_{hi}) + \beta_2^{fej} ln(\hat{P}_f) + X_h + \epsilon_{hi}$$

- Separate coefficients for fuel prices and fuel economy to allow for asymmetrical responses of demand.
- A system in which VKT and fuel efficiency are simultaneously determined to address endogeneity. The estimation technique is 3SLS.

Model structure

$$\overbrace{ln(VKT_{hi})}^{\boxed{\text{Distance}}} = \beta_0^{vkt} + \overbrace{\beta_1^{vkt} ln(P_f)}^{\boxed{\text{Fuel price}}} + \overbrace{\beta_2^{vkt} ln(E_{hi}) + \beta_3^{vkt} ln(E_{hj})}^{\boxed{\text{Fuel economy}}} + X_h + \epsilon_{hi}$$

$$ln(E_{hi}) = \beta_0^{fei} + \beta_1^{fei} ln(VKT_{hi}) + \beta_2^{fei} ln(\bar{P}_f) + X_h + \epsilon_{hi}$$

$$\underbrace{ln(E_{hj})}_{\boxed{\text{Selection bias}}} = \beta_0^{fej} + \beta_1^{fej} ln(VKT_{hi}) + \beta_2^{fej} ln(\hat{P}_f) + X_h + \epsilon_{hi}$$

- Separate coefficients for fuel prices and fuel economy to allow for asymmetrical responses of demand.
- A system in which VKT and fuel efficiency are simultaneously determined to address endogeneity. The estimation technique is 3SLS.
- Correction of selection bias in presence of endogenous explanatory variables(Wooldridge, 2010).

Model structure

$$\begin{aligned} ln(VKT_{hi}) &= \beta_0^{vkt} + \beta_1^{vkt} ln(P_f) + \overbrace{\beta_2^{vkt} ln(E_{hi}) + \beta_3^{vkt} ln(E_{hj})}^{\boxed{\text{Fuel economy}}} + X_h + \epsilon_{hi} \\ ln(E_{hi}) &= \beta_0^{fei} + \beta_1^{fei} ln(VKT_{hi}) + \beta_2^{fei} ln(\bar{P}_f) + X_h + \epsilon_{hi} \\ ln(E_{hj}) &= \beta_0^{fej} + \beta_1^{fej} ln(VKT_{hi}) + \beta_2^{fej} ln(\hat{P}_f) + X_h + \epsilon_{hi} \end{aligned}$$

- The rebound effect takes into account variation in fuel economy of all vehicles in the household :

$$\eta_E(VKT) = \beta_2^{vkt} + \beta_3^{vkt} \times 40\%$$

3SLS estimates of main variables

	VTK_i		E_i		E_j	
VTK_i			0.00403	(0.003)	0.00958	(0.006)
E_i	0.321***	(0.045)				
E_j	-0.0445**	(0.014)				
Rebound Effect	0.305***	(5.74)				
P_f	-0.464***	(0.085)				
Monthly Income	0.110***	(0.022)	0.00568	(0.004)		
Interaction prices and income:	P_f		$\bar{P}_f$		$\hat{P}_f$	
Q2	0.0560	(0.053)				
Q3	0.136*	(0.063)				
Q4	0.296***	(0.070)				
Interaction No of vehicles:			Veh_i		Veh_j	
Log vehicle age - 0			-0.0336***	(0.002)		
Log vehicle age - 1			-0.00457	(0.007)	0.0312*	(0.015)
Log vehicle weight - 0			-0.100***	(0.022)		
Log vehicle weight - 1			0.0270***	(0.004)	0.174***	0.009)
Log horsepower - 0			-0.375***	(0.018)		
Log horsepower - 1			-0.0272	(0.019)	0.429***	(0.023)
Inverse Mill's Ratio	0.136***	(0.012)			-0.0311**	(0.012)
Observations	4698					
R^2	0.616		0.439		0.805	

3SLS estimates of main variables

	VTK_i		E_i		E_j	
VTK_i			0.00403	(0.003)	0.00958	(0.006)
E_i	**0.321*****	(0.045)				
E_j	**-0.0445****	(0.014)				
Rebound Effect	0.305***	(5.74)				
P_f	-0.464***	(0.085)				
Monthly Income	0.110***	(0.022)	0.00568	(0.004)		
Interaction prices and income:	P_f		$\bar{P}_f$		$\hat{P}_f$	
Q2	0.0560	(0.053)				
Q3	0.136*	(0.063)				
Q4	0.296***	(0.070)				
Interaction No of vehicles:			Veh_i		Veh_j	
Log vehicle age - 0			-0.0336***	(0.002)		
Log vehicle age - 1			-0.00457	(0.007)	0.0312*	(0.015)
Log vehicle weight - 0			-0.100***	(0.022)		
Log vehicle weight - 1			0.0270***	(0.004)	0.174***	0.009)
Log horsepower - 0			-0.375***	(0.018)		
Log horsepower - 1			-0.0272	(0.019)	0.429***	(0.023)
Inverse Mill's Ratio	0.136***	(0.012)			-0.0311**	(0.012)
Observations	4698					
R^2	0.616		0.439		0.805	

3SLS estimates of main variables

	VTK_i		E_i		E_j	
VTK_i			0.00403	(0.003)	0.00958	(0.006)
E_i	**0.321*****	(0.045)				
E_j	**-0.0445****	(0.014)				
Rebound Effect	0.305***	(5.74)				
P_f	**-0.464*****	(0.085)				
Monthly Income	0.110***	(0.022)	0.00568	(0.004)		
Interaction prices and income:	P_f		$\bar{P}_f$		$\hat{P}_f$	
Q2	0.0560	(0.053)				
Q3	0.136*	(0.063)				
Q4	0.296***	(0.070)				
Interaction No of vehicles:			Veh_i		Veh_j	
Log vehicle age - 0			-0.0336***	(0.002)		
Log vehicle age - 1			-0.00457	(0.007)	0.0312*	(0.015)
Log vehicle weight - 0			-0.100***	(0.022)		
Log vehicle weight - 1			0.0270***	(0.004)	0.174***	0.009)
Log horsepower - 0			-0.375***	(0.018)		
Log horsepower - 1			-0.0272	(0.019)	0.429***	(0.023)
Inverse Mill's Ratio	0.136***	(0.012)			-0.0311**	(0.012)
Observations	4698					
R^2	0.616		0.439		0.805	

3SLS estimates of main variables

	VTK_i		E_i		E_j	
VTK_i			0.00403	(0.003)	0.00958	(0.006)
E_i	0.321***	(0.045)				
E_j	-0.0445**	(0.014)				
Rebound Effect	**0.305*****	(5.74)				
P_f	-0.464***	(0.085)				
Monthly Income	0.110***	(0.022)	0.00568	(0.004)		
Interaction prices and income:	P_f		$\bar{P}_f$		$\hat{P}_f$	
Q2	0.0560	(0.053)				
Q3	0.136*	(0.063)				
Q4	0.296***	(0.070)				
Interaction No of vehicles:			Veh_i		Veh_j	
Log vehicle age - 0			-0.0336***	(0.002)		
Log vehicle age - 1			-0.00457	(0.007)	0.0312*	(0.015)
Log vehicle weight - 0			-0.100***	(0.022)		
Log vehicle weight - 1			0.0270***	(0.004)	0.174***	0.009)
Log horsepower - 0			-0.375***	(0.018)		
Log horsepower - 1			-0.0272	(0.019)	0.429***	(0.023)
Inverse Mill's Ratio	0.136***	(0.012)			-0.0311**	(0.012)
Observations	4698					
R^2	0.616		0.439		0.805	

3SLS estimates of main variables

	VTK_i		E_i		E_j	
VTK_i			0.00403	(0.003)	0.00958	(0.006)
E_i	0.321***	(0.045)				
E_j	-0.0445**	(0.014)				
Rebound Effect	**0.305*****	(5.74)				
P_f	-0.464***	(0.085)				
Monthly Income	0.110***	(0.022)	0.00568	(0.004)		
Interaction prices and income:	P_f		$\bar{P}_f$		$\hat{P}_f$	
Q2	**0.0560**	(0.053)				
Q3	**0.136***	(0.063)				
Q4	**0.296*****	(0.070)				
Interaction No of vehicles:			Veh_i		Veh_j	
Log vehicle age - 0			-0.0336***	(0.002)		
Log vehicle age - 1			-0.00457	(0.007)	0.0312*	(0.015)
Log vehicle weight - 0			-0.100***	(0.022)		
Log vehicle weight - 1			0.0270***	(0.004)	0.174***	0.009)
Log horsepower - 0			-0.375***	(0.018)		
Log horsepower - 1			-0.0272	(0.019)	0.429***	(0.023)
Inverse Mill's Ratio	0.136***	(0.012)			-0.0311**	(0.012)
Observations	4698					
R^2	0.616		0.439		0.805	

3SLS estimates of main variables

	VTK_i		E_i		E_j	
VTK_i			0.00403	(0.003)	0.00958	(0.006)
E_i	0.321***	(0.045)				
E_j	-0.0445**	(0.014)				
Rebound Effect	**0.305***	(5.74)				
P_f	-0.464***	(0.085)				
Monthly Income	0.110***	(0.022)	0.00568	(0.004)		
Interaction prices and income:	P_f		$\bar{P}_f$		$\hat{P}_f$	
Q2	0.0560	(0.053)				
Q3	0.136*	(0.063)				
Q4	0.296***	(0.070)				
Interaction No of vehicles:			Veh_i		Veh_j	
Log vehicle age - 0			**-0.0336***	(0.002)		
Log vehicle age - 1			-0.00457	(0.007)	0.0312*	(0.015)
Log vehicle weight - 0			**-0.100***	(0.022)		
Log vehicle weight - 1			0.0270***	(0.004)	0.174***	0.009)
Log horsepower - 0			**-0.375***	(0.018)		
Log horsepower - 1			-0.0272	(0.019)	0.429***	(0.023)
Inverse Mill's Ratio	0.136***	(0.012)			-0.0311**	(0.012)
Observations	4698					
R^2	0.616		0.439		0.805	

3SLS estimates of main variables

	VTK_i		E_i		E_j	
VTK_i			0.00403	(0.003)	0.00958	(0.006)
E_i	0.321***	(0.045)				
E_j	-0.0445**	(0.014)				
Rebound Effect	**0.305*****	(5.74)				
P_f	-0.464***	(0.085)				
Monthly Income	0.110***	(0.022)	0.00568	(0.004)		
Interaction prices and income:	P_f		$\bar{P}_f$		$\hat{P}_f$	
Q2	0.0560	(0.053)				
Q3	0.136*	(0.063)				
Q4	0.296***	(0.070)				
Interaction No of vehicles:			Veh_i		Veh_j	
Log vehicle age - 0			-0.0336***	(0.002)		
Log vehicle age - 1			**-0.00457**	(0.007)	**0.0312***	(0.015)
Log vehicle weight - 0			-0.100***	(0.022)		
Log vehicle weight - 1			**0.0270*****	(0.004)	**0.174*****	0.009)
Log horsepower - 0			-0.375***	(0.018)		
Log horsepower - 1			**-0.0272**	(0.019)	**0.429*****	(0.023)
Inverse Mill's Ratio	0.136***	(0.012)			-0.0311**	(0.012)
Observations	4698					
R^2	0.616		0.439		0.805	

Conclusions

- We find that almost one third of fuel savings following an efficiency improvement are lost due to the direct rebound effect.
- We provide further evidence on endogeneity of fuel economy and interdependence of travel distance among vehicles in multivehicle households. Moreover, our model does not support the symmetry assumption.
- Reducing carbon emissions require the combination of energy efficiency improvements with other policies (e.g. taxes, behavioral).
- We will use this model in order to simulate three different policies shocks: prices, fuel economy and income.

Thank you

Estimation of the Rebound Effect for Travel Distance Using Micro-level Data for France

Catherine Benjamin
catherine.benjamin@univ-rennes1.fr

Alejandra Giraldo
deici.giraldo@univ-rennes1.fr