The Rebound Effect

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Conserving Energy

- Conserving energy has high priority on the political agenda:
  - preserves resources for following generations,
  - reduces dependence on energy imports,
  - (allegedly) supports the nuclear-phase out in Germany,
  - reduces CO2-emissions.
- But conserving energy by efficiency increases may have unwanted effects.
- More fuel-efficient cars might lead to more driving and, hence, more congestion, noise or accidents, because driving gets cheaper.

History of the rebound

- Stanley Jevons (1865) first introduced the notion of the energy rebound.
- Jevons was concerned that the industrialization would deplete the British coal reserves.
- He was convinced that more efficient steam engines would increase this process.
- Reason: Higher efficiency reduces operation cost.
- Lower operating cost stimulate the use and the diffusion of technology.
- The steam engine is an example for energy-efficiency improvements that ultimately increase the energy use (Jevons' Paradox).

The energy rebound

- Although a more efficient device uses less energy compared to a less efficient one,
- energy savings might be less than expected because consumers or companies may decide to:
  - use the device more often,
  - use more of these devices,
  - use bigger devices.
- Therefore, the net effect of efficiency gains is unclear a priori.

The environmental rebound

- There may be a trade-off between energy-efficiency and environmental impacts.
- More energy efficient technology may require toxic materials.
  - E.g. mercury in energy saving lamps.
- The production process of more energy-efficient technology might be more energy or transport-intensive.

Rebound pathways

- van den Bergh (2011) identifies 14 distinct mechanisms how the rebound works:
  - Reduced operation cost induce higher usage.
  - Consumers use larger devices or devices with more functions that use more energy.
  - Consumers spend the savings from higher efficiency on additional energy-consuming goods and services.
  - Create new demand for energy-intensive goods.
  - Changes in the factor input mix.
  - Time savings from efficiency gains give the consumer time to spend on other energy uses.
  - . . .

Studied areas

- The direct rebound effect is most often analyzed.
- The most attention when analyzing the direct rebound is given to household auto travel,
- followed by household heating.
- Other household appliances receive considerably less attention.

The dimension on the rebound

- A meta-study by Sorrell et al. (2009) places the rebound for household heating between 1.4% and 60.0%.
- The same study sees the rebound for personal transport between 20.0% and 80.0%.
- Nadel (1993) reports direct rebound effects for lighting and warm water of approximately 10.0% and 0.0%.
- Usually, the short-run estimates of the rebound are considerably smaller than those for the long-run.

Huge variation in the rebound

- Studies vary with respect to the type of data:
  - time-series
  - cross-sectional
  - pooled cross-sectional
  - panel
- The origin of the data
- The level of aggregation varies:
  - aggregate data
  - disaggregate data on the level of the household
- Studies use different definitions of the rebound.
- There is also a time dimension to the rebound effect: short run vs. long run.

Rebound studies by RWI members

- Frondel, M., J. Peters und C. Vance (2008), Identifying the Rebound: Evidence from a German Household Panel, Energy Journal
  - rebound varies between 57% and 67%
- Frondel, M., Vance, C. (2009) Do High Oil Prices Matter? Evidence on the Mobility Behavior of German Households, Environment and Resource Economics
  - rebound varies between 35% and 52%
- Frondel, M., Ritter, N., Vance, C. (2010) Heterogeneity in the Rebound Effect: Further evidence for Germany, Ruhr Economic Papers 227

Research Motivation

- To maintain climate protection policy on track, the European Commission set limits on the allowable per-kilometer CO2 emissions of newly registered automobiles.
- Commission expects that this measure will induce considerable incentives for the development of fuel-saving technologies.

Research Question

- What is the magnitude of the rebound in private car travel demand in Germany?
- Is the rebound heterogeneous with respect to household car travel demand?
- Is the rebound heterogeneous across household types, incomes, . . . ?

Defining the Rebound (1)

- The most natural definition of the direct rebound effect (η) is based on the elasticity of the demand for a particular energy service (s), such as conveyance, with respect to efficiency (μ):

$$\eta_\mu(s) := \frac{\partial \ln s}{\partial \ln \mu} \tag{1}$$

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- But in many empirical studies efficiency data is not available or the data provides only limited variation in efficiencies.
- Even more disconcerting is that observed efficiency increases may be endogenous, rather than reflecting autonomous efficiency improvements.
- Our dataset does not include any instrument for an IV approach.

Defining the Rebound (2)

- Estimates of the rebound effect are frequently based on the negative of the service demand elasticity with respect to service price:

$$\eta_{\mu}(s) = -\eta_{p_s}(s) = -\frac{\partial \ln s}{\partial \ln p_s} \tag{2}$$

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- Definitions 1 and 2 are equivalent if service demand s solely depends on the service price p_s for a given efficiency μ and a constant fuel price p_e.
- The likely endogeneity of efficiency contaminates the estimation of this rebound definition because service price is a conglomerate of efficiency and fuel prices.

Defining the Rebound (3)

- In cases where only data on fuel consumption and fuel prices is available, the empirical estimates are sometimes necessarily based on the negative of own-price elasticity of fuel consumption:

$$\eta_\mu(s) = -\eta_{p_e}(e) = -\frac{\partial \ln e}{\partial \ln p_e} \tag{3}$$

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- Definition 2 and 3 are only equivalent given that three assumptions hold:
  - fuel prices are exogenous,
  - service demand solely depends on the service price,
  - efficiency is exogenous.
- The likely endogenous variable for efficiency needs to be included in any model specification following definition 3.
- Because all three definitions suffer from the same problem, we introduce a fourth definition of the rebound.

Defining the Rebound (4)

- We focus here on a rebound definition that is based on the negative of the fuel price elasticity of transport demand:

$$\eta_\mu(s) = -\eta_{p_e}(s) = -\frac{\partial \ln s}{\partial \ln p_e} \tag{4}$$

- Fuel prices are largely exogenous for individual households.
- Fuel prices typically exhibit sufficient variation.

Data

- The data used in this research is drawn from the German Mobility Panel (MOP 2010), an ongoing travel survey that was initiated in 1994.
- It is organized in overlapping waves, each comprising a group of households surveyed for a period of six weeks in the spring.
- All households that participate in the survey are requested to fill out a questionnaire eliciting general household information, person-related characteristics, and relevant aspects of everyday travel behavior.
- The resulting sample includes 4,097 observations.
- Of the 2,165 households, 962 appear one year in the data, 474 appear two years and 729 appear three consecutive years.

Table 1: Variable Definitions and Descriptive Statistics

Variable Name	Variable Definition	Mean	Std. Dev.
s	Monthly kilometers driven	1,546.32	1,145.93
e	Monthly fuel consumption in liters	94.01	62.86
μ	Kilometers driven per liter	12.97	2.99
p_s	Real fuel price in Euros per kilometer	0.08	0.02
p_e	Real fuel price in Euros per liter	1.01	0.15
# driving licences	Number of driving licences in a household	1.76	0.75
# employed	Number of employed household members	1.03	0.86
vacation with car	Dummy: 1 if household undertook vacation with car during the survey period	0.20	0.40
children	Dummy: 1 if children younger than 19 live in household	0.33	0.47
job change	Dummy: 1 if an employed household member changed jobs within the preceding year	0.13	0.33
multi-car households	Dummy: 1 if an household has more than one car	0.35	0.48
population density	People per square km in the county in which the household is situated	835.97	1004.40

Model Specification

- We estimate the following model specification:

$$\ln(s_{it}) = \alpha_0 + \alpha_{p_e} \cdot \ln(p_{e\,it}) + \alpha_{\mathbf{x}}^T \cdot \mathbf{x}_{it} + \xi_i + \nu_{it} \ , \qquad (5)$$

- where the logged monthly vehicle-kilometers traveled, $\ln(s)$, is regressed on logged fuel prices, $\ln(p_e)$, and a vector of control variables $\mathbf{x}$.
- Subscripts i and t are used to denote the observation and time period, respectively.
- ξ_i denotes an unknown individual-specific term, and ν_{it} is a random component that varies over individuals and time.
- The rebound effect is obtained by the negative estimate of the coefficient α_{p_e} on the logged fuel price.

Random Effects

- We estimate our model using random-effects and quantile methods.
- We choose to employ random-effects methods for three reasons:
  - Random-effects methods also allow for the estimation of coefficients of time-invariant variables.
  - The fixed-effects estimator fails to estimate the coefficients of variables that do not vary much within a household over time.

Quantile Regression

- We choose to employ quantile methods because:
  - Quantile regression provides a more complete picture of the relationship between the dependent variable and the regressors at different points in the conditional distribution.
  - It allows us to study the impact of a regressor such as fuel prices on the full distribution of the dependent variable.

OLS and panel vs. quantile regression

- OLS and panel estimation return an average rebound effect by estimating the conditional expectation function:

$$E(\ln(s_{it}|p_e, \mathbf{x}_{it})) = \alpha_0 + \alpha_{p_e} \cdot \ln(p_{e\,it}) + \alpha_{\mathbf{x}}^T \cdot \mathbf{x}_{it} \tag{6}$$

- Quantile regression indicates the variability in the households' responses to fuel price changes, depending upon the level of distance traveled:

$$Q_\tau(\ln(s_{it}|p_e, \mathbf{x}_{it})) = \alpha(\tau) + \alpha_{p_e}(\tau) \cdot \ln(p_{e\,it}) + \alpha_{\mathbf{x}}^T(\tau) \cdot \mathbf{x}_{it} + F_{\varepsilon_{it}}^{-1}(\tau) \tag{7}$$

.

Table 2: pooled OLS, Median Regression and Random-Effects Results

	pooled OLS		Median Regression		Random Effects	
	Coeff.s	Std. Errors	Coeff.s	Std. Errors	Coeff.s	Std. Errors
$\ln(p_e)$	** -0.694	(0.073)	** -0.618	(0.064)	** -0.574	(0.063)
children	0.043	(0.030)	0.003	(0.028)	* 0.065	(0.027)
logged income	** 0.127	(0.039)	** 0.194	(0.048)	* 0.077	(0.032)
# *driving licenses*	** 0.082	(0.020)	** 0.052	(0.018)	** 0.079	(0.019)
# *employed*	** 0.161	(0.017)	** 0.162	(0.016)	** 0.128	(0.016)
job change	* 0.072	(0.032)	* 0.079	(0.038)	0.051	(0.029)
vacation with car	** 0.301	(0.023)	** 0.288	(0.027)	** 0.252	(0.020)
population density	** -0.064	(0.013)	** -0.068	(0.000)	** -0.073	(0.013)
multi-car households	** 0.466	(0.029)	** 0.476	(0.026)	** 0.456	(0.028)
constants	** 5.625	(0.282)	** 5.212	(0.355)	** 6.059	(0.235)

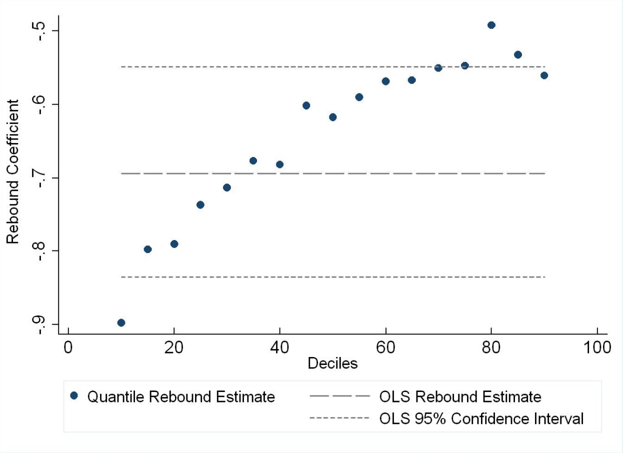
* denotes significance at the 5 %-level, ** at the 1 %-level.

Table 3: Quantile-Regression Estimates

	$Q_{10}(\ln(s))$ Coeff.s	Std. Errors	$Q_{30}(\ln(s))$ Coeff.s	Std. Errors	$Q_{70}(\ln(s))$ Coeff.s	Std. Errors	$Q_{90}(\ln(s))$ Coeff.s	Std. Errors
$\ln(p_e)$	** -0.898	(0.116)	** -0.714	(0.076)	** -0.551	(0.080)	** -0.561	(0.088)
children	** 0.129	(0.045)	* 0.060	(0.029)	-0.015	(0.032)	-0.048	(0.033)
logged income	0.050	(0.068)	** 0.183	(0.042)	** 0.170	(0.045)	0.071	(0.049)
# driving licenses	** 0.197	(0.035)	** 0.103	(0.018)	0.024	(0.019)	0.032	(0.021)
# employed	** 0.208	(0.031)	** 0.160	(0.016)	** 0.149	(0.018)	** 0.129	(0.021)
job change	-0.053	(0.055)	** 0.079	(0.035)	** 0.107	(0.031)	** 0.099	(0.042)
vacation with car	** 0.380	(0.044)	** 0.332	(0.026)	** 0.249	(0.027)	** 0.152	(0.030)
inhabitant density	** -0.081	(0.015)	** -0.078	(0.011)	** -0.060	(0.015)	** -0.043	(0.013)
multi-car households	** 0.377	(0.046)	** 0.465	(0.029)	** 0.478	(0.032)	** 0.539	(0.038)
constants	** 5.203	(0.478)	** 4.902	(0.307)	** 5.746	(0.330)	** 6.880	(0.358)
Observations used	4,097		4,097		4,097		4,097	

* denotes significance at the 5 %-level, ** at the 1 %-level. Standard errors are calculated using bootstrap.

Figure 1: OLS and Quantile Regression Results for the Rebound



Conclusions from our paper

- Because increases in fuel efficiency effectively decrease the unit costs of driving, their effectiveness in reducing emissions may be offset by increased demand for car travel.
- Drawing on household level data from Germany, the present study employs panel, and quantile regression techniques to estimate the magnitude of the rebound effect as well as to explore the degree of its heterogeneity across households.
- Results from the quantile regression suggest some heterogeneity according to driving intensity, with the estimated rebound ranging from a low of 50% in the 80%-quantile to a high of 90% in the 10%-quantile.
- From a policy perspective, the fact that the estimated rebound is relatively high irrespective of driving intensity calls into question the effectiveness of efficiency standards as a pollution control instrument.

General conclusions

- The existence of the rebound effect is generally accepted.
- Changes in efficiency usually trigger changes in the behavior of households and firms.
- The magnitude of the rebound effect is unclear:
  - different data and aggregation levels
  - varying rebound definitions
  - systematic differences between countries
  - varying methodologies
- However, a host of studies estimate direct rebound effects of considerable size.
- The direct rebound is the most often analyzed, but not the only rebound effect.
- The frequently high estimates of the rebound call into question the efficiency of programs to reduce energy consumption by efficiency gains.