

Contents lists available at ScienceDirect

Transportation Research Part A

journal homepage: www.elsevier.com/locate/tra

Estimating the price elasticity of fuel demand with stated preferences derived from a situational approach

Reinhard Hössinger^a, Christoph Link^a, Axel Sonntag^b, Juliane Stark^{a,*}^a Institute for Transport Studies, University of Natural Resources and Life Sciences, Peter Jordan Str. 82, 1190 Vienna, Austria^b Vienna Center for Experimental Economics, University of Vienna, Oskar-Morgenstern-Platz 1, 1090 Vienna, Austria

ARTICLE INFO

Article history:

Received 19 July 2016

Received in revised form 18 May 2017

Accepted 5 June 2017

Available online 13 June 2017

Keywords:

Price elasticities

Fuel demand

Stated preference

Choice experiment

Discrete choice modelling

ABSTRACT

An evidence-based policy debate about future fuel demand requires reliable estimates for fuel price elasticities. Such predictions are often based on revealed preference (RP) data. However, this procedure will only yield reliable results in the absence of severe structural discontinuities. In order to overcome this potential limitation we used a situational stated preference (SP) survey to estimate the response to hypothetical fuel price changes beyond the scope of previous observations. We elicit fuel price elasticities for price increases up to four Euros per liter and find that the situational approach predicts the actual responses to previously observed fuel price changes very well. We conclude that applying a situational approach is particularly useful, if behavioral predictions for unprecedented (non-monetary) policy interventions or supply side shocks are of interest that go beyond the reach of standard RP approaches.

© 2017 The Authors. Published by Elsevier Ltd. This is an open access article under the CC BY-NC-ND license (<http://creativecommons.org/licenses/by-nc-nd/4.0/>).

1. Introduction

Climate protection goals, strategic energy security and reducing local emissions are good reasons why policy makers might have a vivid interest in reducing fossil fuel consumption. It is therefore no surprise that much attention has been paid to the transport sector and its dependency on fossil fuels, particularly since the crude oil shocks in the 1970s and thereafter. Independent of the specific fuel consumption target, it is crucial to have a good understanding of how the fuel demand would react to (policy induced) fuel price changes. This article complements the literature by proposing a *situational* stated preference approach to provide a complementary tool for estimating fuel price elasticities, particularly for unprecedentedly high fuel price increases.

The fuel price elasticity of demand is typically derived from revealed preference (RP) data (for a recent application see [Odeck and Johansen, 2016](#)). This technique is feasible if the environment is sufficiently stable. However, RP estimates imply an extrapolation from the range of past variation. If the environment changes dramatically in terms of new options or a fundamental change of circumstances, this may cause biased results ([Ortúzar and Willumsen, 2011](#)). In this paper, we argue that especially when the conditions of fuel consumption are expected to change drastically, using a stated preference survey that takes behavioral choice constraints into account (situational approach) could be a valuable complementary estimation technique. In fact, the situational approach has already successfully been applied in other disciplines but, to our knowledge, has not been used to estimate the effect of fuel price increases on fuel demand of private households. This paper is the first to

* Corresponding author.

E-mail addresses: reinhard.hoessinger@boku.ac.at (R. Hössinger), christoph.link@boku.ac.at (C. Link), axel.sonntag@univie.ac.at (A. Sonntag), juliane.stark@boku.ac.at (J. Stark).

contrast results from estimating fuel price elasticities from aggregate consumption data (RP) with a particular version of a stated preference approach (SP) which considers important situational constraints to travel decisions such as trip chains, passengers, weather conditions, etc. as well.

We found that the elasticity estimates derived from our situational SP approach very well correspond with actually observed demand behavior. We discuss the merits of both approaches and conclude that the higher effort of using a SP method might be well invested if behavioral predictions for unprecedented price increases or non-monetary policy interventions are of interest.

Section 2 briefly reviews estimates of fuel price elasticity in the literature and Section 3 explains the situational approach in detail. Section 4 describes the used sample and the estimated models and Section 5 presents simulation results of fuel demand. Finally, Section 6 discusses the results and Section 7 concludes with the main findings of the paper.

2. Background

The magnitude of the price elasticity of fuel demand is subject of an extensive debate in both the academic and the policy realm (Frondel and Vance, 2010). A key issue of concern is the uncertainty of estimation caused by the complex nature of fuel demand. It is the result of lots of different decisions, each of which is influenced by many factors. Whether or not a car trip will be replaced or omitted in response to an increasing fuel price does not only depend on the cost, but also on situational factors such as trip purpose, time pressure, luggage or passengers to carry, weather conditions, etc. Given that travel decisions are strongly related to other household decisions, activity-based models are a promising approach to better understand the travel behavior within the context of overall time and budget allocation.

In the realm of fuel demand models, Johansson and Schipper (1997) introduced a concept that we followed in our work. They estimated the long term fuel demand for cars based on aggregate data of 12 OECD countries. Importantly, the total demand was evaluated by separately estimating total vehicle stock, mean fuel intensity, and mean annual driving distance. Based on this seminal contribution, Brons et al. (2008) picked up the idea for a meta-analytical study of the price elasticity of gasoline demand. They decomposed the total fuel demand of passenger road transport into three different elasticities: car ownership, fuel economy (specific fuel consumption of the vehicle), and travel demand. This is still an over-arching framework; each of the three elasticities is an aggregate of many different reactions. More fuel economy for instance can be achieved by purchasing a hybrid car, using the more fuel efficient car among those cars available in the household (De Borger et al., 2016a), or driving in fuel saving mode. The possible reactions to reduce car travel demand are even more versatile: switching to car passenger or transit, driving to a closer destination, staying at home, etc. Related to that, Austin and Dinan (2005) emphasized an important difference between fuel economy and travel demand, when they estimated the costs of reducing gasoline consumption by increasing corporate average fuel-economy (CAFE) standards. The maximum gasoline savings would be realized only after all existing vehicles were replaced (14 years in their model), whereas a gasoline tax would produce greater immediate savings by encouraging people to drive less. Considering the above, we describe how we operationalized the individual parts of our framework in Section 4.1.

When it comes to data commonly used for estimating the price elasticity of fuel demand, Dargay (2007) distinguishes two sorts of RP data: panel data and aggregate time-series data, made up of observations over long periods of time of large groups of individuals. In a meta-analysis of 69 primary studies covering both kinds of data sources, Goodwin et al. (2004) found that short term elasticities range from -0.01 to -0.57 , but only a small part of this range could be assigned to specific factors such as exposure time (short term vs. long term), different countries, and different years of measurement.

Table 1 lists several RP estimates of price elasticities of fuel demand reported in the literature. They are based on a wide range of geographical areas, mostly focusing on North America, and some of them are rather advanced in age. The table distinguishes between short term and long term responses and also between disaggregate and aggregate data sources. According to Goodwin (1992) and Goodwin et al. (2004), short term responses are those made within one period, while long term refers to the asymptotic end state when responses are completed; in most cases periods of 5–10 years, within which the greatest change happens in the first 3–5 years. Other authors such as Puller and Greening (1999) distinguish between changes in travel demand (short term) and changes in vehicle stock (long term).

With respect to the level of aggregation it is well recognized that estimates derived from aggregate data face severe limitations: They ignore that different individuals may have diverging consumption responses to the same price fluctuations (Wadud et al., 2010a, 2010b). Consequently, a fuel tax can impose critical hardship on parts of the population (Kayser, 2000), even if the average response suggests a moderate effect. The hardship will likely cause political barriers to implementation. Despite this limitation, it seems that the average elasticity estimates of disaggregate and aggregate data sources do not differ systematically from each other on a *ceteris paribus* basis. This is important for our study, which includes a comparison of elasticity estimates from disaggregate and aggregate data (see Section 5).

It is however well documented that the price elasticity of fuel demand varies a lot with respect to many other dimensions. For example, Huntington (2010) found that a new all-time high has a larger effect than sub-maximum changes, i.e. price cuts and recoveries. The population group makes a difference, too. According to Kayser (2000) rural households and those with no public transport available are more resistant to higher fuel prices than those in an urban setting and with access to public transport. Wadud et al. (2009) found the elasticity to follow a U-shape across five different income groups, while De Borger et al. (2016b) report a decreasing fuel price elasticity of driving demand among groups with higher income. Moreover, Dahl

Table 1
Price elasticities of fuel demand reported in the literature, by average year of observation.

Source	Observation period	Average year	Geographic region	Elasticity of fuel demand		Data type ^A
				Short term	Long term	
Archibald and Gillingham (1980)	1972–1973	1972	USA	–0.43	–	D
Goodwin et al. (2004) ^a	1974–1981	1978	Worldwide	–0.35	–0.93	A, D
Hughes et al. (2008) ^b	1975–1980	1978	USA	–0.275	–	A
Dahl (2012) ^{a,c}	1954–2005	1980	Worldwide	–0.15	–0.55	A, D
Dahl (2012) ^{a,d}	1954–2005	1980	Worldwide	–0.10	–0.33	A, D
Kayser (2000) ^b	1981	1981	USA	–0.23	–	D
Puller and Greening (1999)	1980–1990	1985	USA	–0.35	–	D
Hymel et al. (2010)	1966–2004	1985	USA	–0.075	–0.361	A
Brons et al. (2008) ^a	1972–1999	1986	Worldwide	–0.36	–0.81	A, D
Goodwin et al. (2004)	1981–1991	1986	Worldwide	–0.16	–0.43	A, D
Brännlund and Nordström (2004)	1985–1992	1989	Sweden	–	–0.98	D
Sentenac-Chemin (2012) ^c	1978–2005	1991	USA	–	–0.3	A
Havranek et al. (2012) ^{a,c}	1974–2011	1993	Worldwide	–0.09	–0.31	A, D
Wadud et al. (2009)	1984–2003	1994	USA	–0.266	–	A
Odeck and Johansen (2016)	1980–2011	1995	Norway	–0.26	+0.09	A
Hirota et al. (2003)	1990–2002	1996	Worldwide	–0.195	–	A
West and Williams (2007)	1996–1998	1997	USA	–0.51	–	D
Romero-Jordán et al. (2010)	1998–2001	2000	Spain	–	–0.55	D
Wadud et al. (2010a)	1997–2002	2000	USA	–	–0.473	D
Austin and Dinan (2005)	2001	2001	USA	–	–0.39	A
Lin and Prince (2013) ^e	1990–2012	2001	USA	–0.03	–0.239	A
Burguillo et al. (2017)	1998–2005	2001	Spain	–0.35 to –0.49 ^e	–	D
Burke and Nishitaten (2013) ^e	1995–2008	2002	worldwide	–	–0.2 to –0.5	A
Hughes et al. (2008) ^b	2001–2006	2004	USA	–0.056	–	A
Hymel et al. (2010) ^b	2004	2004	USA	–0.055	–0.285	A

^a Meta study (otherwise primary study).

^b Focus on periods with high fuel price variation.

^c Analysis based on gasoline consumption only.

^d Analysis based on diesel consumption only.

^e Estimated mixture of short- and long-run elasticities.

^A Data type: A – aggregated, D – disaggregated.

(2012) reports different price elasticities for gasoline and diesel consumption, and Knittel and Sandler (2015) find that drivers of vehicles with high fuel consumption are more responsive to increasing fuel prices.

Furthermore, three prevailing patterns of variability evolve from Table 1: (i) The price elasticities differ across countries (see also Graham and Glaister, 2002a; Goodwin et al., 2004, and Gillingham, 2014) and US estimates are in most cases lower than worldwide or European estimates from a comparable period of time. (ii) The price elasticity also changed over time. Before and during the oil crises in the 1970s all studies found relatively high elasticities both in the short and long run, which also refers to recent higher gasoline price changes as shown by Gillingham (2010) for the elasticity of vehicle-miles-traveled in period 2005–2008 in California, USA. Studies based on more recent periods find lower magnitudes. Hughes et al. (2008) mention several possible reasons for the decline: changing land-use patterns, more fuel efficient vehicles, the growth of multiple income households and per capita disposable income, and downgrade of public transport supplies. (iii) Studies which focus explicitly on periods with high fuel price fluctuation find lower elasticities than other studies of a broadly comparable time frame, which cover periods of low price variation or steadily falling prices. 1981 was the last year with strongly fluctuating prices following the oil supply shock of the late 1970s (Kayser, 2000). Since then, fuel prices have fallen gradually in real terms until 2003. The studies of Hughes et al. (2008) and Hymel et al. (2010) are the first of the ‘new generation of volatility’. These observations are important, because our aim is to estimate the response to radical fuel price increases beyond past experience.

Given this manifold contingency of the price elasticity of fuel demand, it seems important that our SP estimates are compared to those RP estimates, which are derived (i) from the same geographical area, (ii) from a broadly comparable period of time (see also Gillingham et al., 2014), and (iii) from a comparable segment of the population, which can either be a representative sample or the same subgroup.

Recent extensions to the state-of-the-art were made by Glerum et al. (2015) and Gillingham et al. (2015) who both develop dynamic models for household’s joint decision regarding car ownership, car selection and car usage based on register data on car ownership. However, they do not report elasticity figures for fuel demand.

The stated preference (SP) technique, in particular in the form of discrete choice experiments, is a ‘trade mark’ of transportation research. It is usually employed to reveal respondent’s presumed behavior in hypothetical situations, which can refer to policy scenarios (Espino et al., 2007), new transport services (Hensher and Rose, 2007) or alternative fuel vehicles (Dagsvik et al., 2002 as well as Mabit and Fosgerau, 2011). Given the widespread use of SP surveys, it is surprising that they were rarely employed to estimate the elasticity of fuel demand as a response to hypothetical prices. We found only one

example from [Sipes and Mendelsohn \(2001\)](#). They examined the stated responses to higher gasoline prices ranging from 1.70 to 5.80 \$ per gallon in a survey with 500 people in Southern California and Connecticut between 1999 and 2000. The interviewees were asked how many miles they would drive in response to the price increase both instantaneously and after some time to make adjustments. Using a double-log functional form, they found a price elasticity of fuel demand of -0.35 and -0.59 in the short and long run, respectively. The authors conclude “that drivers are price inelastic (...) [and that] imposing environmental surcharges on gasoline will result in only a small reduction in driving” ([Sipes and Mendelsohn, 2001, p.299](#)). However, in a letter to the editor, [Comeau and Chapman \(2002, p.317\)](#) “consider a 23% emissions reduction resulting from a 33% tax to be quite significant”. We share this view. Given the figures in [Table 1](#) for the USA around the year 2000, these estimates are even higher than expected. One reason for the high elasticity may be that [Sipes and Mendelsohn \(2001\)](#) did not account for situational restrictions, which may prevent drivers from changing their behavior, even if they intended to do so. Furthermore, the exclusive focus on monetary aspects can evoke biased estimations, because households rarely analyse their fuel costs in a systematic way ([Turrentine and Kurani, 2007](#)). The SP experiment does not only have to provide information about the fuel price, but also take the situational constraints into account, which can interfere with purely economic considerations. The situational approach applied in this paper addresses this problem. It tests the individual response to a stimulus in consideration of situational constraints, which limit the scope of available options. Transport-related decisions are particularly dependent on situational opportunities and constraints. [Train and Wilson \(2008\)](#) emphasize that SP experiments should be constructed from a choice, which the respondent made in an actual RP setting (SP-off-RP experiment). This procedure enhances the realism of the SP task and the efficacy of preference revelation. The situational approach is an additional step toward more realism: it is not only about choice options that exist in reality, but also about actually realized trips.

3. The situational approach

The situational approach is based on the idea that human judgments are not only dependent on internal (cognitive) factors, but also on external (situational) factors ([Schamber et al., 1990](#)). It is understood as “a theoretical viewpoint that emphasizes the importance of the environmental situation, rather than his or her innate personality disposition, in determining a person’s behavior” ([Kent, 2006](#)). This concept was successfully applied in many fields of research such as consumer studies ([Dubois and Laurent, 1999](#)), environmental studies ([Corraliza and Berenguer, 2000](#)), evaluation research ([Hall, 2004](#)), and in management theory, where it constitutes the situational leadership theory ([Chemers, 2000](#) as well as [Vroom and Jago, 2007](#)).

Transport-related applications of the situational approach are rare. Some early contributions stem from [Brög \(1982\)](#) as well as [Brög and Erl \(1983\)](#). In a later article, [Goulias et al. \(1998\)](#) analysed the objective and subjective constraints that trip makers face using a trip-by-trip panel analysis. The behavioral dimensions (situations) were found to be general constraints, system constraints, service constraints, lack of information, negative disposition, time, comfort, and cost. The presence of these situations was in turn explained by objective characteristics of the trip maker such as place of residence, household resources, and trip characteristics. Different individual perceptions (of the same objective situation) were found to constitute a strong ‘unobserved heterogeneity’, which limits the quality of behavioral models if ignored. [Goulias \(2000\)](#) further emphasized that the situational approach should start from detailed respondent debriefings to identify the reasons why a person made specific choices (the situational dimensions), which are then expressed in terms of objective and subjective constraints. This procedure provides more accurate information about trip rates and the underlying preference structure.

However, the situational approach is not only about analyzing more variables. It is also about making the experimental choice situation as similar as possible to those situations, which respondents experience in their everyday life. The situational approach tries to respect the complexity directly during measurement. It is not necessary to know all relevant factors; the important thing is that they become effective during the choice situation. This procedure will not yield a fully parameterized model, which can estimate the behavioral response to a changing situational context (e.g. weather conditions), but it should provide more reliable estimates of the price elasticity of fuel demand than a conventional SP survey, and this is still something worth noting. Each scenario refers to a concrete situation in a hypothetical environment, rather than a hypothetical situation in a hypothetical environment. It shifts the choice makers’ focus from “what would you do if...?” to “what would you have done in this specific situation, if...?”. As an example, a respondent faced with a hypothetically increased fuel price may answer that he would basically use the bus instead of the car, but not for that specific trip, because he had to bring his mother. Situational factors can affect decisions in both directions, but in most cases they are restrictions to changes, thus supporting a continuation of past behavior. Ignoring the situational factors could therefore result in overly strong reactions to a stimulus, because respondents tend to forget the restrictions associated with behavioral changes.

The situational approach has serious implications for the way of conducting a survey. The SP scenarios must be based on real life trips to capture the situational factors, which might influence the choices. In that sense, the situational approach differs from a standard SP survey along the following characteristics. First, the SP survey is usually advanced by a trip diary ([Goulias, 2000](#)) which can be completed by telephone or in a written survey. The trips reported in the diary form the basis for the development of the scenarios. Second, situational factors have to be integrated when preparing the scenarios (individual car travel costs due to different fuel consumption per vehicle, public transport opportunities, etc.). Third, the respondents need a thorough introduction to ensure that they take the situational factors into account when making their choices.

4. Data collection and analysis

4.1. Concept of measurement

Our survey followed the idea of [Johansson and Schipper \(1997\)](#) as well as [Brons et al. \(2008\)](#), who defined three elasticities, which sum up to the total elasticity of fuel demand of passenger transport (see Section 4.3). These elasticities (or levels of decisions) were measured as follows. First, changes in car ownership were measured by a car ownership scenario, which was carried out for each car in the household with the corresponding owner (or most frequent user). The possible reactions to the increasing fuel price are shown in [Table 2](#). The option ‘sell the car without replacement’ indicates a change in car ownership. Second, changes in fuel economy were measured by the same scenario. The option ‘replace the car’ indicates the willingness to replace the existing car by a more fuel efficient car. The consumption level of the new car that people would probably choose was taken from the literature. It was not measured in the survey, because this question can hardly be answered by consumers alone. It must also account for vehicle supply and technology. Third, changes in travel demand were measured by two different types of scenarios ([Table 2](#)): (i) Each respondent performed up to four daily trip scenarios with 7 response options. (ii) Each household, who reported a car holiday trip within the last year, performed a holiday trip scenario with five response options. This distinction was based on the experience that holiday trips follow a different rationale, but can still account for a considerable share of total fuel demand.

These scenarios cover the major, but not all dimensions of behavioral responses to a fuel price change. One potential limitation is that we had only one indicator for a change in fuel economy, i.e. purchasing a more fuel-efficient car. Other options such as fuel saving driving or the preferred use of fuel-efficient cars in the household may also contribute to lower the consumption level, but they were not included in the survey not to over-burden the respondents. Our respondents performed several tasks concerning mode choice for their daily trips resulting in multiple observations per respondent. Similarly, there could be more than one observation per respondent in the car ownership tasks, if the individual owned more than one car. However, this was rarely the case. We discuss the econometric implications of this design feature in Section 4.3.

4.2. Survey design

We conducted the survey considering the requirements of a situational approach as described in Section 3. The sample is representative for Austrian households with at least one car trip in the week of survey. We defined that our sample should provide sufficient statistical power to identify a single effect size (correlation coefficient) of 0.1 at a probability of $\alpha = 0.05$ with a statistical power of $(1 - \beta) = 0.8$. This setting yields a sample size of 617 according to a power analysis described by [Anderson \(2003\)](#). We further assumed that each respondent completes three “daily trip” scenarios on average, so that the sample should comprise around 200 individuals.¹ The net sample includes 188 households with 230 respondents and 313 cars. They reported 502 daily trips and 113 long distance holiday trips by car. The overall response rate was 32%.²

The survey was conducted in several steps. It was announced by a postcard followed by a telephone call. Respondents who belonged to the target group and agreed to participate in a subsequent face-to-face interview, completed three blocks of questions on the phone. First, each member of the household completed a diary of his/her car trips at the most recent working day and weekend, respectively. The survey instrument is a variant of the KONTIV-format ([Brög et al., 1983](#)), which had been used by the authors successfully in previous studies. The diary asked for origin, destination, trip purpose, trip duration, specification of the used car, and further situational factors such as weather conditions and car passengers, separated according to members and non-members of the household. This bundle of characteristics formed the respondents’ situational framework for their mode choice. Second, a similar diary was completed for the most recent long distance holiday trip of the households. Third, information about all cars available in the household (annual mileage, fuel type, fuel consumption) as well as intended changes in the vehicle stock (purchase, replacement, and/or sale) was collected. The answers given by telephone provided the basis for the development of stated choice experiments, which were customized to the respondents’ specific situations.

The face-to-face interviews aimed at involving all adult household members. At least the main users of all cars in the household were asked to be present. The interviews started with the introduction of a credible fuel price increase. To avoid strategic answers, respondents were told that we were interested in drivers’ reactions, if a fuel price rally, as it happened in summer 2008, would happen again, maybe even more seriously and lasting longer. Three different stated response scenarios followed this announcement (see [Table 2](#)); an example of a scenario is presented in [Appendix A \(Fig. A1\)](#).

The first scenario was dealing with daily trips. The car trips were summarized to car journeys that include all car trips between leaving and arriving at home. A maximum of four car journeys out of those reported in the telephone interview were selected for the face-to-face interview. Respondents, who were mostly but not necessarily the car owners, were reminded of these trips by an easy-to-read summary sheet to mentally put them back in the trip situation. They were asked for their reasons for using a car and their general willingness to use other modes than a car. All attributes of the journey were left unchanged in the scenario, with the exception of the fuel price which was changed hypothetically and could take four different values: 1.5, 2.0, 3.0, or 4.0 € per liter, presented in a random order. Since the fuel price was the only attribute that was

¹ The “daily trip” scenarios were considered as main scenarios and therefore taken as reference for the power analysis. The model described in Section 4 comprises additionally a “car ownership” model and a “holiday trip” model with lower sample size and, therefore, lower statistical power (see [Table 4](#)).

² More detailed sample characteristics are presented in [Tables OA1 and OA2 of the online appendix](#).

Table 2

Overview of scenarios in the in-depth interview.

No.	Basis	Scenario	Alternative response options
(1) Car use on daily trips (car journeys ^a)			
a–d	Up to four car journeys ^b (2 last working days, 1 last Saturday, 1 last Sunday)	Change of fuel costs and effect on journey costs Additional information about the effect on annual running costs for all cars per household based on annual mileage	<ul style="list-style-type: none"> • Remain with the car • Switch to public transport • Switch to bicycle • Switch to car-passenger • Avoid making this trip • Choose another destination • Other reaction
e	Car journey (randomly chosen from a–d)		
(2) Car use on holiday trips			
	Most recent holiday journey by car	Change of fuel costs and effect on journey costs	<ul style="list-style-type: none"> • Remain with the car • Avoid making this holiday trip • Choose another destination • Switch to another mode • Other reaction
(3) Car ownership			
	Existing car(s)	Change of fuel costs and effect on annual running costs based on annual mileage	<ul style="list-style-type: none"> • Keep the car • Sell the car without replacement • Replace the car by a car with lower fuel consumption

^a A car journey was defined as all trips by car between leaving and arriving at home.

^b Scenarios a–d had random order. A maximum of four journeys per person was selected. If there had been less than 4 car journeys less scenarios were conducted. If there were no car journeys last Saturday/Sunday, car journeys at a working day were selected instead, if possible.

varied in the choice set, an orthogonal or efficient survey design was not applicable (cf. Ortúzar and Willumsen, 2011). The respondents received an additional sheet that showed each reported trip along with the following information: (i) increased costs of the car trip following from the higher fuel price; (ii) the best possible public transport option for this trip, if any available and (iii) the possible response options (see Table 2). Those who stuck to the car were informed about the cumulative increase of annual running costs due to the higher fuel price and were then asked to reconsider their decision. This task should capture travel demand reactions after people had realized the long run consequences of the higher fuel price. The second part of the interview was dealing with the holiday trip, if any reported. The choice experiment was similar to the one used for daily trips, but somewhat shorter: the interviewees had only 5 response options and no distinction was made between instantaneous and ‘long run’ response. The third part focused on decisions that would affect car ownership and vehicle fuel consumption. Again assuming a hypothetically increased fuel price, car owners were asked how they would get on with their vehicles. For each available car they could choose between 3 options: keeping the car, selling the car without a replacement, or replacing it by a car with lower fuel consumption. Finally, respondents were asked for some demographic information.

4.3. Model development

Based on the survey experiments, we developed a model that estimates the total fuel demand of passenger road transport in dependence of the fuel price. Our model follows Brons et al. (2008), who decomposed the elasticity of total fuel demand of passenger transport into three different elasticities:

$$\varepsilon_{FD} = \varepsilon_{CO} + \varepsilon_{FE} + \varepsilon_{TD}$$

where ε denotes the price elasticity with regard to the total fuel demand FD , car ownership CO , fuel economy (specific fuel consumption of vehicle) FE , and travel demand TD . We estimated these elasticities by a series of disaggregate choice models. Based on the assumption of an increasing fuel price, these models predict the choice probabilities of car users with regard to (i) selling the car; (ii) replacing it by a more fuel efficient car; and (iii) omitting individual car trips, which could be daily trips or long distance holiday trips. The choice options in this model have a nominal scale type. We thus used a multinomial logit approach for parameter estimation. The underlying random utility theory assumes a deterministic and a stochastic component of utility U , which is associated with each choice option i for individual n :

$$U_{in} = V_{in} + \eta_{in} \quad \text{with} \quad V_{in} = \sum_{k=1}^K \beta_{ik} x_{ink} \quad (1)$$

The deterministic utility component V_{in} depends on a parameter vector β_{ik} and the values of k independent variables. These variables can be alternative-specific such as travel time and cost, which vary with the chosen mode – or none alternative-specific; the latter variables refer to the choice situation (day time, trip purpose, etc.), to the choice maker (gender, age, etc.), or to his/her background (income, residential area, etc.). The choice options available in a given situation form the choice set. The stochastic component η in includes uncertainties due to unobserved factors and measurement errors. Assuming that η_{in} is Gumbel-distributed, we used a multinomial logit model to calculate the choice probabilities associated with each alterna-

tive option i of the choice set. The choice-maker is assumed to choose the option with the highest utility U . The model assumes a logistic relationship between independent variables and choice probability. This has serious consequences for the comparison with RP estimates, which are commonly specified by a double-log functional form (see Section 5).

We developed three independent discrete choice models of this type: a model of car ownership, a model of daily trip demand and a model of holiday trip demand. A combined (nested) model of car ownership and use was not feasible, because both decisions were obtained from different choice experiments and partly different respondents (car ownership decisions from car owners, mode choice models from car users). The car ownership model and holiday trip model are multinomial logit models with fixed parameters, because the underlying data include only one choice per respondent. The data for the daily trip model include several (usually three) repeated choices per respondent, resulting in a pseudo-panel structure. Repeated choice tasks are used in most conjoint surveys. [Bliemer and Rose \(2011\)](#) report a review of 61 choice experiments, 59 of which had repeated choices, usually between 4 and 16. Treating repeated choices in the same way as cross-sectional data, i.e. assuming independence between the choices of the same respondent, may not be appropriate ([Hess and Rose, 2009](#)) because such a procedure can result in upward biased standard errors for the estimated parameters ([Ortúzar and Willumsen, 2011](#)). However, [Ortúzar et al. \(2000\)](#) tested a random coefficient Probit model against a classical Multinomial Logit, finding that most parameter values decreased, in some cases considerably, but sometimes also increased; the t-ratios decreased in general as expected. Current practice is that the estimation of repeated choices can be handled by a Mixed Logit model (ML), which is an extension of the multinomial logit that allows for taste variation between individuals. It should yield unbiased parameter estimates even in the case of pseudo-panel data. We used a ML for the mode choice model of daily trips. The ML includes additional stochastic components η_i , which allow the parameters to vary across individuals with zero mean. The choice probabilities are calculated using the integral of the logit formula over the density of η ([Train, 2003](#)).

The total fuel demand was modelled on the basis of single trips d . The daily trip demand and holiday trip demand was estimated in different models (see [Table 4](#)), but the formal structure was the same in both cases: the models of car ownership, trip demand, and fuel consumption of new cars were merged as shown in Eq. (1). It is a time series model with time periods t representing consecutive months, because several effects caused by a higher fuel price accumulate over time: (i) car ownership according to the sales rate; (ii) the fuel consumption of available vehicles according to the replacement rate along with the fuel consumption of newly purchased vehicles; and (iii) the daily trip demand, which changes incrementally due to increasing awareness of the cumulative costs of a higher fuel price.

$$FD_{dt} = (1 - P(s)_{ct}) \left(\frac{P(k)_{ct}}{P(k)_{ct} + P(r)_{ct}} FEa_{c,t-1} + \frac{P(r)_{ct}}{P(k)_{ct} + P(r)_{ct}} FE n_{ct} \right) P(c)_{dt} L_d \quad (2)$$

FD_{dt} predicted fuel demand of trip d in period t ;

$P(s)_{ct}$ probability that car c has been sold before or in period t ;

$P(k)_{ct}$ probability that car c is kept in period t ;

$P(r)_{ct}$ probability that car c is replaced by a new car in period t ;

$FEa_{c,t-1}$ fuel consumption of available car c in former period;

$FE n_{ct}$ fuel consumption of new car c , if purchased in period t ;

$P(c)_{dt}$ probability of using a car for trip d in period t ;

L_d length of trip d .

The similarity with the three elasticities of [Brons et al. \(2008\)](#) is clearly visible in Eq. (1): The 1st term represents changes in car ownership, the 2nd term changes in fuel economy, and the 3rd term changes in travel demand, which is obtained by multiplying the trip length with the probability of using a car for this particular trip. There are some explicit relationships between the three elasticity components, which are mediated through model parameters (see [Table 4](#)). They cause for instance that the probability of using a car is dependent on whether the car is kept or replaced. Correlations between the error components of the involved models are not considered. We followed [Giuliano and Dargay \(2006\)](#), who argue that a high independence of decisions can be argued by a sequential decision-making process. Whereas household car ownership is a medium-term decision given longer-run choices, individual travel is the outcome of short-term decisions, given household car ownership. In this case, conventional estimation techniques obtain efficient parameter estimates. Otherwise, more complex discrete-continuous model systems would need to be applied (see [Spissu et al., 2009](#) as well as [Castro et al., 2012](#)).

Since forecasting all aspects of fuel efficiency, including fuel consumption of a new car that people would choose, given they decided to replace their existing car, would have gone beyond the scope of this article, it was not elicited with the survey, but taken from literature. [Table 3](#) shows some elasticity estimates of vehicle fuel efficiency in the literature. The estimates refer to changes of the vehicle stock, so that the long term estimates better reflect the response with regard to new vehicles. However, they cover also aspects of fuel efficient driving or selection of a car in multi-car households, while studies focusing just on the replacement of cars conclude in lower elasticities of fuel efficiency such as [Gillingham \(2012\)](#) or [Klier and Linn \(2013\)](#). The decreasing time trend in the long term estimates suggests that the current estimate might well be below 0.3. For our estimations, we used the average of short and long term estimates of 0.26.³

³ Note that in our simulations, we do not distinguish whether higher fuel economy is caused by more efficient driving or technological advancements (in case of buying a new car).

Table 3

Elasticity estimates of fuel efficiency of vehicles with regard to the fuel price.

Source	Short term	Long term
Graham and Glaister (2002b)	0.10	0.46
Goodwin et al. (2004)	0.15	0.40
Brons et al. (2008)	0.14	0.31

Table 4

Parameter estimates of the discrete choice models (t-values shown in brackets).

Kind of model Subject of decision	Car ownership Available cars in the household		Daily trips Daily trips of household members			Holiday trips Latest holiday trip of household
	Replace	Sell	Car	Public	Other	Other
Choice options in scenarios						
Alternative specific constant	−1.746** (−2.34)*	−4.677** (−2.61)*	–	−3.394** (−4.36)*	−0.353** (−1.11)	−1.819** (−1.93)*
Fuel price in € per liter	0.396** (2.16)*	0.906** (2.20)*	–	–	–	0.894** (2.93)*
Car travel costs in € – before long term awareness	–	–	−0.081** (−3.51)*	–	–	–
Car travel costs in € – after long term awareness	–	–	−0.144** (−5.20)*	–	–	–
Annual car travel distance in 1000 km	0.059** (2.75)*	−0.131** (−2.01)*	–	–	–	–
Trip purpose = no working or business trip	–	–	–	0.209** (0.48)	0.846** (3.41)*	–
Trip duration in minutes (reference = car)	–	–	–	−0.001** (−0.20)	−0.018** (−4.12)*	–
Car passenger(s) = yes	–	–	–	−1.061** (−2.38)*	0.636** (2.93)*	–
Number of car passengers	–	–	–	–	–	−0.930** (−3.23)*
Car purchase price in 1000 €	–	–	–	−0.005** (−0.24)	−0.049** (−4.76)*	–
Excepted current value of the car in 1000 €	−0.082** (−3.17)*	−0.069** (−1.19)	–	–	–	–
Car fuel type = gasoline (otherwise diesel)	–	–	–	–	–	0.770** (1.38)*
Public transport season ticket = yes	0.784** (2.16)*	−5.849** (−0.44)*	–	2.281** (5.44)*	0.294** (0.94)	–
Educational level (equidistant numbers)	–	–	–	−0.217** (−1.29)	−0.284** (−3.04)*	–
Employment status = full time job	–	–	–	0.893** (1.91)*	0.065** (0.32)	–
Number of adults living in the household	−0.296** (−2.02)*	0.430** (1.52)*	–	–	–	–
Residential area = Vienna	–	–	–	−0.615** (−1.14)*	−0.620** (−1.92)*	−1.106** (−1.74)*
Residential area = medium-sized town	1.449** (2.80)*	1.857** (1.96)*	–	–	–	–
Standard deviation of random parameters						
Car travel costs in € – before long term awareness			0.0001** (0.00)			
Car travel costs in € – after long term awareness			0.0237** (0.34)*			
Number of observations	306		657			113
Log likelihood	−185.55		−411.928			−51.14
Rho squared (Nagelkerkes/Cragg & Uhlers)	0.22		0.58			0.32
Ratio of right predicted	75%		73%			79%

** Levels of significance: $p < 0.01$; the baseline category is 'keeping the car' in the car ownership model and 'using the car' in the daily trips model and holiday trips model.

* Levels of significance: $p < 0.05$; the baseline category is 'keeping the car' in the car ownership model and 'using the car' in the daily trips model and holiday trips model.

The total fuel demand in a given month t was estimated from the fuel demand of individual trips using the sample enumeration method (Ortúzar and Willumsen, 2011). The aggregation procedure accounts for the weights of the sample units and for different repetition rates of working day trips, weekend trips, and long distance holiday trips.

$$FT_t = \sum_{p=1}^P \sum_{d=1}^D FD_{pdt} \cdot W_p \cdot Rd + \sum_{h=1}^H FD_{ht} \cdot W_h \cdot \frac{1}{Rh} \quad (3)$$

FT_t predicted total fuel demand in period t ;

P total number of people p in the survey;

D total number of daily trips d reported by person p ;

FD_{pdt} predicted fuel demand of daily trip d in period t , which was reported by person p ;

W_p weight of person p who reported trip d ;

Rd average monthly repetition rate of daily trips (16.67 for working day trip; 3.33 for weekend trip);

H total number of households h in the survey;

FD_{ht} predicted fuel demand of the holiday trip in period t , which was reported by household h ;

W_h weight of household h who reported the holiday trip;

Rh 12 if the last holiday trip was made within the last 12 months, otherwise number of months elapsed since the holiday trip

The predicted fuel demand at a fuel price of 1.0 € per liter (the price level during the survey period) represents the baseline fuel demand of 100%. Changes in demand due to changes in the fuel price are calculated in percent of the baseline. Responses to a price of up to 4.0 € per liter were covered by the survey. The total fuel demand FT_t in Eq. (2) includes all kinds of fossil fuels. The model accounts for different consumption rates, but makes no difference between gasoline and diesel, because both had a similar price during the survey period (although the car trip costs that respondents were faced with in the survey were calculated also considering the fuel type in order to strictly follow the situational approach).

The weights W_p (weight of people in the daily trips model) and W_h (weight of households in the holiday trips and car-ownership model) were calculated prior to the analysis in order to make the results representative for the Austrian population. Households were weighted according to their size (number of household members), number of available cars, and settlement type. Persons were weighted according to gender, age, settlement type, and the combined distribution of trip length and trip purpose. The trip features were transferred into personal features by means of dummy coding, where a dummy indicated if a person had reported at least one trip of a specific combination of length and purpose. The exogenous distribution of these characteristics in the general population was taken from publicly available Austrian statistics (Herry and Sammer, 1998; Statistik Austria, 2010).

4.4. Parameter estimates

Table 4 shows the results of the three discrete choice models of car ownership, daily trips, and holiday trips. The daily trip model includes three options, although the scenario had seven response options (see Section 4.1). ‘Remaining with the car’ and ‘changing to public transport’ constitute separate options. All other responses were combined to ‘other’, because they had too low counts to be represented as separate alternatives. This applies to using a bicycle or becoming a car-passenger, choosing another destination, omitting the trip, and doing anything else. The fuel demand of all other answers than ‘remaining with the car’ was set to zero. This procedure is consistent for all cases except when drivers changed the destination or switched to carpooling, but these cases are rare (6 and 11 out of 495 choices, respectively). Table 4 includes no column for keeping the car in the car ownership model and for car use in the holiday trips model, because these are the reference options with zero parameters. Due to using the situational approach we had a very large number of possible predictors – more than 200, if log-transformed variables and dummies for nominal categories are counted separately. Table 4 lists only those predictors, which bear a significant influence on the responses in at least one of the three models, and were thus included in the model. A hyphen means that the predictor was either not applicable in the respective model (e.g., trip attributes in the car ownership model) or had no significant effect, and were therefore not included in the final model.

The fuel price and the car travel costs (which are derivatives of the fuel price) affect the choices in the expected direction in all three models. The car travel costs appear twice in the daily trip model. The parameter ‘after awareness of long term costs’ reflects the lagged effect on travel demand due to increasing cost awareness. Table 4 further reveals two effect chains, which run between the three models in the combined approach outlined in Eq. (1). The first effect chain corresponds to the rebound effect. A replacement of the car by a more fuel-efficient car reduces the car travel cost, and lower car travel cost in turn increase the probability of using a car for daily trips. The second effect chain starts with the omission of single car trips due to higher car travel costs, which reduce the annual car travel distance, that in turn increases the probability that the car is sold at all. All three models include several predictors, which refer to ‘situational circumstances’ such as trip purpose, trip duration, existence of car passengers (daily trips), and number of car passengers (holiday trips).

5. Elasticity estimates and simulated fuel demand

The choice models of Table 4 can be used to estimate the response to an increasing fuel price with respect to car ownership, vehicle fuel efficiency, and travel demand. We obtain the total fuel demand by merging these components as shown in Eq. (2). We now contrast the elasticity estimate of the SP survey with an RP estimate.

Previous estimates of the price elasticity of fuel demand, among other relations, suggest an influence of the geographical region (Goodwin et al., 2004) as well as the period of time (Hughes et al., 2008). Consequently, in addition to the breadth of revealed preference estimates from the literature (see Table 1) that, with few exceptions, focused on North America or at a global scale; in the following we provide a revealed preference estimation for Austria. We used aggregate monthly Austrian demand and price data of gasoline and Diesel from October 2002 to December 2011 (BMWfJ, 2013) and we obtain a short term elasticity estimate of $\beta_1 = -0.135$ which reassuringly fits well into the range of previous RP estimates (see Table 1).⁴

In the following, we use the symmetric elasticity estimate stated above to predict the change in fuel consumption for a period of increasing fuel price – and compare the prediction with the actually observed fuel consumption during this period. For this exercise, we chose the period from February 2007 until April 2008, in which the fuel price started at a low level (1 Euro per liter) and monotonically increased in the following months. In order to control for the strong seasonality of the data, we computed the 12 months moving average for both fuel price and fuel consumption.⁵ The smoothed price is 1.00 Euro per liter at the beginning of the period and reaches 1.25 Euros per liter in April 2008 (+25%) before falling later on. The double log model with an elasticity of -0.135 predicts a 3.4% drop in consumption to 96.6% of the initial level. In comparison, in the same period, the observed fuel demand dropped by 4.4–95.6% of the initial consumption (from initially 825 Billion to 788 Billion liters).

Fig. 1 shows a comparison of SP and RP results. The two bold lines refer to the SP estimates. The dashed line indicates the immediate response, which causes a demand reduction to 62% at a fuel price of 4.0 € per liter. The solid line indicates the effect after one year, when consumers became fully aware of the cumulative annual running costs and had some time to replace their vehicles by more fuel efficient ones, or sell cars. We find that full awareness is responsible for an additional reduction in fuel demand, resulting in a total drop to 40% of the base level. The logic behind the two lines is as follows: If the fuel price would increase to a certain level and remain at this level, the fuel demand would drop immediately to the dotted line and afterwards moving continuously downwards to the solid line within the first year of exposure. The RP and the situational approach predict an almost identical response for a moderate price change from 1.00 to 1.25 Euros per liter. Although the actually observed change in consumption (95.6% – diamond in Fig. 1) is marginally closer to the SP estimate (96.7%), the estimation based on the RP approach results in almost the same prediction (97.0%).

The SP model described in Eq. (2) is a time series model, so that the fuel demand not only depends on the fuel price, but also on exposure time. Fig. 2 shows a model application, in which the fuel price is set to 2.0 € per liter and remains at this level over a period of 5 years to indicate the progress over time. The travel demand (dashed line) decreases immediately to 90% and then further to 85% of the base level within the first year. Afterwards, the awareness effect is exhausted and the rebound effect comes to the fore. The increasing availability of fuel-efficient cars reduces car travel costs and makes car use more attractive again. As a result, travel demand rises slowly, reaching 87% after 5 years. The fuel demand (solid line) shows the same immediate decrease, but the increasing availability of fuel-efficient vehicles opens a gap between travel and fuel demand. The rebound effect does however not outweigh the fuel savings, so that the total fuel demand decreases further over the whole period, reaching 80% of the initial level after 5 years.

Fig. 3 illustrates the time-dependent mechanisms of the changes in fuel demand for the examples of a fuel price of 2 and 2.5 € per liter. Note, that Fig. 3 displays the decrease of fuel demand, i.e. a lower bar represents to a lower decrease, i.e. an actual increase in fuel demand. As already shown in Fig. 2, the immediate response for such a price shock to 2 € per liter is a decrease in travel demand for daily and holiday trips of 10% (17% for 2.5 € per liter) while there will be no immediate change in the vehicle fleet. After one year, the aforementioned awareness effect has fully developed its impact on the mobility behavior with a further decrease of fuel demand by 5% (10% for 2.5 €). Additionally, the reduction (sold cars without replacement) has slowed down after 12 months while the renewal of the vehicle fleet is ongoing since the average fuel consumption approaches asymptotically to a not yet reached level. After 60 months, fleet renewal is still ongoing. These new cars induce a rebound effect on fuel demand, leading to an increase of fuel demand over time. The rebound effect amounts to 2% (fall in demand is reduced from 15% to 13%) and 3% (fall in demand is reduced from 27% to 24%) for a price of 2 and 2.5 € per liter, respectively. However, after 60 months, the entire fuel demand is clearly below its level after the immediate effect.

⁴ See Appendix C for details on the regression models used. In addition to the standard symmetric model we also obtained estimates for asymmetric demand elasticities (separate elasticity estimates for rising and falling prices) and also distinguished between periods of economic recovery and recession. Note further that the estimation of the RP counterfactual is based on the total Austrian fuel consumption. Due to data limitations it was not possible to distinguish fuel consumption for private passenger cars from any other type of fuel consumption. In that sense, the obtained estimate most likely represents a lower bound for the elasticity of private fuel consumption, because the demand of large institutional (e.g. public railways, military) and industrial (e.g. large road transport fleets) consumers is typically much less elastic than of private households (for a comprehensive meta study see Litman, 2006). A graphical representation of the data used for our RP estimation can be found in the online appendix (Figs. OA1 and OA2).

⁵ The moving average at month t is calculated as the weighted sum of observations of 6 months in the past and 6 months ahead such that $\bar{P}_t = \frac{1}{12} \sum_{i=t-6}^{t+6} P_i \forall i \neq t$ and $\bar{C}_t = \frac{1}{12} \sum_{i=t-6}^{t+6} C_i \forall i \neq t$.

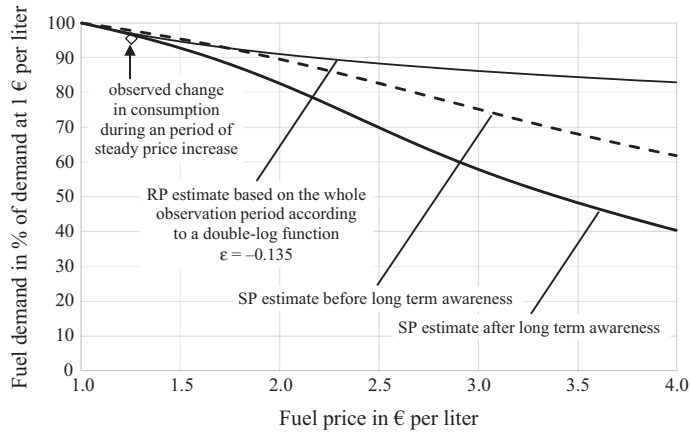


Fig. 1. Comparison of SP and RP elasticity estimates of fuel demand with regard to changes of the fuel price. Please note: The three lines represent predictions, whereas the diamond indicates an actual observation, i.e., a decrease in fuel consumption due to rising fuel prices from 1 to 1.25 Euros per liter [own figure].

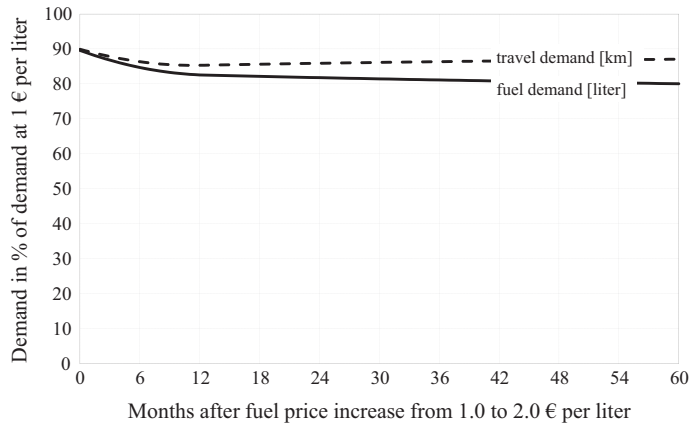


Fig. 2. Predicted progress of travel demand and fuel demand after an increase of the fuel price from 1.0 to 2.0 € per liter [own figure].

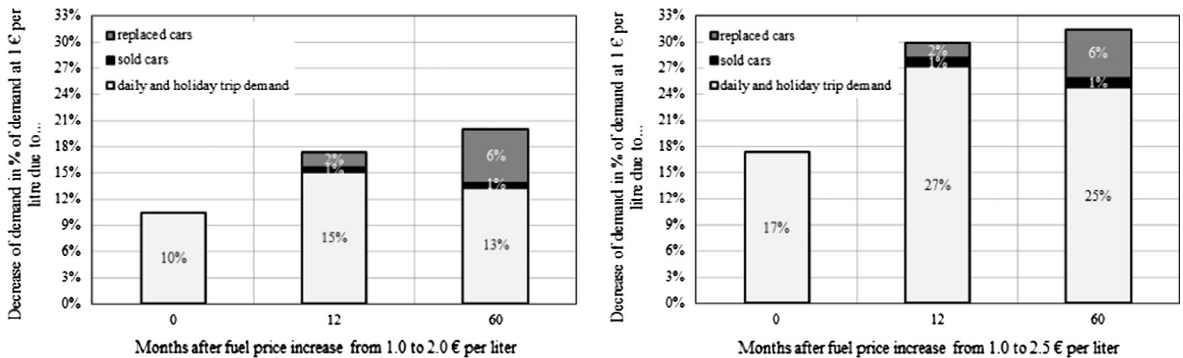


Fig. 3. Mechanisms of decreasing fuel demand after an increase of the fuel price from 1.0 to 2.0 € per liter (left) and 2.5 € per liter (right) [own figure].

Table 5

Fuel price elasticities of fuel demand in dependence of fuel price level and exposure time.

Fuel price in € per liter	Immediate response	Response after 1 year	Response after 5 years
1.5	−0.116	−0.185	−0.245
2.0	−0.159	−0.276	−0.321
2.5	−0.208	−0.391	−0.422
3.0	−0.259	−0.498	−0.525
3.5	−0.307	−0.581	−0.612
4.0	−0.347	−0.656	−0.688

Finally, for better comparability with the literature, the simulated fuel demand was converted into elasticities by using a standard double-log elasticity definition of $\varepsilon = \ln(Q)/\ln(P)$. Table 5 shows a series of such elasticity estimates at different fuel price levels and different exposure times.

In line with previous elasticity estimations (see Table 1), we find that, for any given price level, long term elasticities are consistently larger in magnitude than those for the short term. This is not surprising, since demand has more time to react to a new, increased price level. Furthermore, we find that fuel price elasticities increase with the price level. This is an interesting finding and is only made possible by what we consider one of the strengths of a situational stated preference approach, namely that, in contrast to standard SP approaches, one can analyze fuel price changes beyond the magnitude of previous observations, yet, taking important situational constraints into account. The intuition is that while fuel demand will already decrease to some extent with moderate price rises, more substantial reactions like selling the car or moving closer to the workplace are more likely to occur if the price level succeeds a certain threshold.

6. Discussion

We conducted a SP survey and developed a series of discrete choice models in order to estimate the elasticity of fuel demand of passenger road transport with regard to a radical fuel price increase beyond the level of previous variation. The fuel price assumed in the hypothetical scenarios ranged from 1.5 to 4.0 Euros per liter. The price elasticity is expressed by a logistic function. If translated to a double log function, which is commonly used for RP elasticity estimates, our short term elasticity would range from −0.12 to −0.35; the long term elasticity from −0.25 to −0.69.

In methodological terms, the study is a test of a SP survey in a specific design (the situational approach) using RP results as a benchmark. The findings are promising. Our estimates of the price elasticity of fuel demand match very well with actually observed changes in fuel demand, at least within the range of past fuel price variation, for which observations are available. Despite the seemingly high estimated elasticities for higher price levels, we consider our estimates to represent a lower bound. This is because our model only accounts for a limited set of reactions in terms of selling the car, replacing it by a more fuel-efficient car, or avoiding to use a car for daily trips or holiday trips. For example, Bomberg and Kockelman (2007), who provide a good overview in which ways people adapt to increasing fuel prices, distinguished a total of 12 response categories such as driving the most fuel efficient vehicle, paying attention to vehicle maintenance, carpooling, driving at slower speeds, shopping around for the best gas price (the favorite response), etc. Many of these aspects that potentially could increase demand elasticities are not included in our model.

An important factor, which affects the long term response to fuel price changes in particular, is the rebound effect. Using Sorrell et al.'s (2009, p. 1359) definition that “a rebound effect of 20% means that [...] 20% of the potential energy savings are ‘taken back’ as a result of the increased demand for energy services” we find a rebound effect of 4.3% after one year and 11.9% after 5 years for a fuel price of 1.5 € per liter. Interestingly, higher price levels yield smaller rebound effects. For example, with a fuel price of 3.5 € per liter, the rebound effect amounts to 3.7% after one year and to 12.3% after five years (see Table D1 in Appendix D for more details). That is because for very high prices levels, even driving a more fuel-efficient car is very expensive which consequently reduces demand. Under such conditions, only indispensable trips are still made by car.

Small and Van Dender (2007) estimate a rebound effect of 4.4% in the short term and 22.2% in the long term, based on US panel data of the period 1966–2001. Using a recent extension of the data series up to 2009, Hymel and Small (2015) find a short term rebound effect of 4.7 and a long term effect close to 30%. Sorrell et al. (2009) conclude in their meta-analysis that the long-term rebound effect is between 10% and 30%. Our short term estimate matches perfectly with these RP results, but the long term estimate is at the lower edge. That is because we potentially underestimated the changes caused by ‘other reactions’, which are not considered in our model.

Overall, we suggest two methodological improvements of the situational approach used in this paper. First, the question of vehicle fuel efficiency should not be limited to changes in the vehicle stock (selling or replacing vehicles), but it should additionally account for behavioral changes such as fuel saving driving or the preferential use of economical cars, if available in the household. Second, the influence of the fuel price on the fuel economy of purchased vehicles needs an explicit research focus, which includes both sides of purchase transactions. Regarding the latter point, for future research, it would be inter-

esting to investigate which vehicles car manufacturers would offer and which vehicles consumers would buy among those for sale. However, this is only of moderate concern regarding our estimation. The deviation of our SP estimates from revealed fuel price reactions is rather low.

In consequence, we are confident that the situational approach, in principle, is a suitable tool for exploring consumers' reactions, particularly to scenarios that reach beyond the range of previous experience. It is important to understand behavioral patterns, and how they interact, more broadly to propose suitable policy recommendations. For example, in contrast to prior studies, [West and Williams \(2007\)](#), in an attempt to calculate the optimal second-best gasoline tax level, find that gasoline consumption is a relative economic complement to leisure. Therefore, an optimal gasoline tax would be significantly higher than the marginal damages caused by gasoline use (even if there were no externalities associated with gasoline use at all).

However, that is not to say that fuel taxes are an outlived policy option. Rather, and despite the availability of a rich set of alternative measures, e.g. consumption-based registration taxes, distance-based road pricing, parking schemes or incentives for the purchase of zero emission vehicles, classical instruments such as fuel taxes will continue to play an important role to control fuel consumption ([Romero-Jordán et al., 2010](#)).

Importantly, the scenarios in the situational approach are not limited to monetary changes but can incorporate non-monetary changes as well, such as changing market conditions or disruptive technologies like a breakthrough in battery technology, which extends the range of electric vehicles. Although RP approaches, to some extent, could exploit previous structural (non-monetary) discontinuities (e.g. urban vehicle restrictions) as well, these changes are likely to be very situation-specific and hard to extrapolate.

An additional use-case of SP experiments is the in-depth analysis of differences between population segments, which can be a limitation of pure RP approaches where such demographic characteristics are often not observed jointly with actual fuel consumption. Along these lines, [Kockelman and Kalmanje \(2005\)](#) estimated the public response to a credit-based congestion pricing (CBCP) by means of a survey of 500 individuals. Values of travel time and trip flexibility varied greatly across respondents. Women (relative to men), younger persons, those without children, and with fewer vehicles were more likely to modify their travel behavior rather than paying the toll. Trips to work or school were found to be particularly inelastic.

Since the main aim of this article was to implement a situational stated preference survey to elicit fuel price elasticities, and to compare the predictions with actual demand behavior, we did not conduct a counterfactual standard SP survey. Nevertheless, it would be interesting to put the predictive quality of the relatively costly situational approach in perspective with the results obtained with a standard SP approach. Clearly, more research is needed to get a better understanding to what extent the stated preferences derived from a situational approach can produce reliable behavioral predictions for a wide range of scenarios.

7. Conclusions

Revealed preference estimations of fuel price elasticities are considered a reliable method to predict behavioral demand responses in sufficiently stable environments, in which the situation in the forecast period does not differ substantially from the period the elasticity estimates are based on. In order to overcome this potential limitation we used a situational stated preference (SP) survey to estimate the response to hypothetical fuel price changes beyond the scope of previous observations. In contrast to standard stated preference surveys the situational approach tries to take additional behavioral constraints into account and does not ask purely hypothetically “What would you do if...?” but more specifically “What would you have done in this specific situation if...”. Reminding respondents of actual situations in their own recent past helps them consider personal constraints when deliberating about their response to a fuel price increase. We found that, overall, the situational approach predicted the actual aggregate responses to previously observed fuel price changes very well. Our results suggest that the situational SP approach is especially useful for estimating demand responses to a steep and lasting price increase, as it may result from policy interventions or from changing market conditions such as demand and supply side shocks. In summary, we argue that both RP and SP approaches have their merits. The higher procedural costs of using a situational SP method might be well-invested if behavioral predictions for unprecedented situations such as radically increasing prices or non-monetary policy interventions are of interest.

Acknowledgements

We would like to thank two anonymous Reviewers for their comments and suggestions and are grateful to Will Barker, Stefania Sitzia and Alexander K. Wagner for valuable comments at various stages of the work described here. This work was financially supported by Kommunalkredit Public Consulting from the budget of the Austrian Climate and Energy Fund [A760657].

Appendix A. Sample description of the SP survey

See Fig. A1.

EB3	Scenario 1: Daily car trips			person	JS: <input checked="" type="checkbox"/>
	Contact-ID: P12	Car: 1	Name: John Smith	Order:	


Assumption:	Fuel price increases to	1.50	€/ litre
--------------------	-------------------------	------	----------

Day: Saturday	Date: 29/08/2009	Journey: 1	Car nr.: 1
---------------	------------------	------------	------------

Journey details:

Total distance: 8.5 km

Total duration: 40 min



Impact of the increasing fuel price:

The fuel costs for this journey increase from 0.85 € to 1.28 €.
Old New

How would you most probably react?
 Please explain your decision.

No change (remain with the car)	<input type="checkbox"/>	→	<input type="text"/>
Choose another destination	<input type="checkbox"/>	→	<input type="text"/>
Avoid making this trip	<input type="checkbox"/>	→	<input type="text"/>
Join a carpool for this trip	<input type="checkbox"/>	→	<input type="text"/>
Switch to public transport for this trip	<input type="checkbox"/>	→	<input type="text"/>
Take the bike for this trip	<input type="checkbox"/>	→	<input type="text"/>
Others, please specify	<input type="checkbox"/>	→	<input type="text"/>

Explanation:

Fig. A1. Example of a scenario in the in-depth interviews [own figure]. Note: The questionnaire was shown to the respondent, but had to be filled in by the interviewer.

Appendix B. Historical trend of fuel demand in Austria

See Fig. B1.

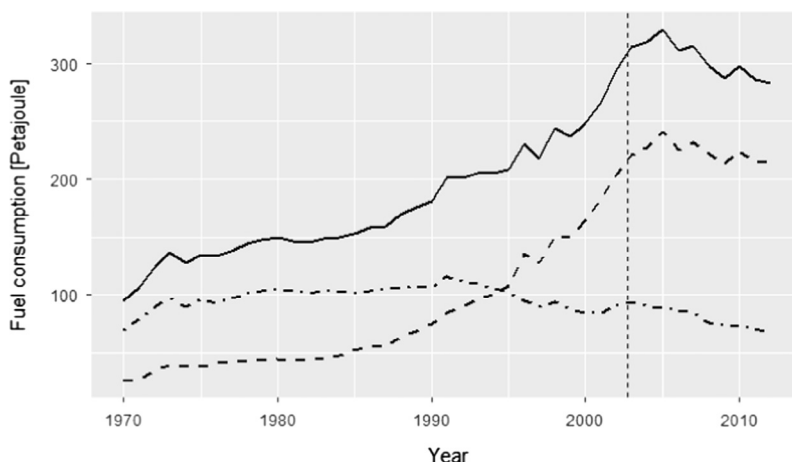


Fig. B1. Fuel consumption in Austria between 1970 and 2012 [own figure]. Note: Gasoline (dash-dotted) and Diesel (dashed) consumption add up to the total fuel consumption (solid line). In this paper we only used consumption data from October 2002 to December 2011 (to the right of the vertical dashed line). Source: Energy balances Austria 1970–2012, [Statistik Austria \(2013\)](#).

Appendix C. Revealed preference estimation of Austrian fuel price elasticities

In order to provide an RP estimate for Austrian fuel demand data, we first applied a standard double log specification ([Ajanovic and Haas, 2012](#); [Hughes et al., 2008](#)). This specification also controls for real GDP and uses monthly dummies to capture the strong seasonality of the data.

$$\ln C_{jt} = \beta_1 \ln P_{jt} + \beta_2 \ln Y_{jt} + \sum_{j=1}^{11} m_j d_j + \varepsilon_{jt} \quad (\text{C1})$$

C_{jt} fuel (gasoline and diesel) consumption in month j and year t ;

P_{jt} real fuel price in Euros per liter in month j and year t ;

Y_{jt} real GDP per capita in month j and year t ;

d_j dummy of month j (1 if month = month i , otherwise zero)

m_j estimated seasonal component of month j ;

ε_{jt} i.i.d. error term

For the whole observation period from October 2002 to December 2011 we obtain an elasticity estimate of $\beta_1 = -0.135$ (see model 1 in [Table C1](#)) which fits well into the range of previous RP estimates (see [Table 1](#)).

In addition to estimating one price elasticity of fuel demand, in a second specification, we allowed for asymmetric prices responses, i.e. estimated one fuel price elasticity for rising prices β_{1r} and another one for falling prices β_{1f} . We chose a specification that directly elicits the fuel price elasticity for each region of price changes. In Eq. (C2) β_{1r} denotes the price elasticity for price increases whereas β_{1f} stands for the elasticity of falling prices. Other than that, this specification is identical to (C1).

$$\ln C_{jt} = \beta_{1r} \ln P_{jtr} + \beta_{1f} \ln P_{jtf} + \beta_2 \ln Y_{jt} + \sum_{j=1}^{11} m_j d_j + \varepsilon_{jt} \quad (\text{C2})$$

Distinguishing demand reactions on rising and falling prices, very much in line with previous findings, reveals that demand reacts slightly stronger to price increases than to a reduction in fuel prices, although not significantly so (model 4, F-test: $p = 0.823$).

As a third step, we investigated whether the general economic environment (recovery or recession) affects the price elasticity of fuel demand. For this exercise, we computed the moving average – as defined in Footnote ⁴ in the main text of this article – of the real GDP per capita. We then estimated the Eqs. (C1) and (C2) for those periods where the smoothed GDP per capita increased and those periods where it decreased separately. Overall, demand turns out to be more elastic in recovery rather than recession periods, and particularly so for falling prices (see model 5 in [Table C1](#)).

Table C1
OLS regression results.

	(1) Full	(2) Recovery	(3) Recession	(4) Full	(5) Recovery	(6) Recession
Price	−0.135 [*] (0.0685)	−0.192 [*] (0.0989)	−0.0126 (0.131)			
Price (rising)				−0.131 [*] (0.0759)	−0.157 (0.108)	−0.000990 (0.168)
Price (falling)				−0.117 [*] (0.0691)	−0.240 ^{**} (0.114)	−0.0158 (0.138)
GDP per capita	−0.179 (0.199)	−0.106 (0.251)	−0.686 (0.498)	−0.216 (0.189)	−0.106 (0.252)	−0.700 (0.527)
January	−0.0996 ^{***} (0.0242)	−0.123 ^{***} (0.0305)	−0.0660 (0.0642)	−0.101 ^{***} (0.0244)	−0.130 ^{***} (0.0317)	−0.0667 (0.0667)
February	−0.0746 ^{***} (0.0243)	−0.0771 ^{**} (0.0315)	−0.0939 (0.0560)	−0.0765 ^{***} (0.0243)	−0.0786 ^{**} (0.0317)	−0.0937 (0.0579)
March	0.0752 ^{***} (0.0248)	0.0708 ^{**} (0.0327)	0.0712 (0.0559)	0.0725 ^{***} (0.0249)	0.0734 ^{**} (0.0329)	0.0721 (0.0584)
April	0.105 ^{***} (0.0229)	0.0917 ^{***} (0.0300)	0.133 ^{**} (0.0511)	0.104 ^{***} (0.0231)	0.0950 ^{***} (0.0303)	0.134 ^{**} (0.0544)
May	0.120 ^{***} (0.0230)	0.100 ^{***} (0.0336)	0.157 ^{***} (0.0430)	0.119 ^{***} (0.0231)	0.104 ^{***} (0.0340)	0.157 ^{***} (0.0446)
June	0.140 ^{***} (0.0231)	0.157 ^{***} (0.0335)	0.145 ^{***} (0.0435)	0.139 ^{***} (0.0232)	0.151 ^{***} (0.0342)	0.146 ^{***} (0.0453)
July	0.185 ^{***} (0.0228)	0.158 ^{***} (0.0313)	0.251 ^{***} (0.0463)	0.184 ^{***} (0.0231)	0.161 ^{***} (0.0315)	0.252 ^{***} (0.0505)
August	0.165 ^{***} (0.0229)	0.157 ^{***} (0.0299)	0.165 ^{***} (0.0518)	0.164 ^{***} (0.0233)	0.160 ^{***} (0.0303)	0.167 ^{***} (0.0555)
September	0.171 ^{***} (0.0228)	0.162 ^{***} (0.0299)	0.190 ^{***} (0.0515)	0.171 ^{***} (0.0230)	0.157 ^{***} (0.0304)	0.191 ^{***} (0.0538)
October	0.186 ^{***} (0.0220)	0.175 ^{***} (0.0284)	0.222 ^{***} (0.0630)	0.190 ^{***} (0.0223)	0.171 ^{***} (0.0288)	0.223 ^{***} (0.0657)
November	0.0635 ^{***} (0.0220)	0.0582 [*] (0.0294)	0.0704 (0.0512)	0.0635 ^{***} (0.0222)	0.0579 [*] (0.0295)	0.0706 (0.0530)
Constant	6.077 ^{***} (1.790)	5.441 ^{***} (2.264)	10.59 ^{**} (4.470)	6.407 ^{***} (1.698)	5.434 ^{***} (2.270)	10.71 ^{**} (4.735)
Observations	111	69	29	111	69	29
R-squared	0.794	0.826	0.836	0.794	0.828	0.836

Note: Models 1 and 4 were estimated using the full range of observations (Oct 2002–Dec 2011). Models 2 and 5, and models 3 and 6 were estimated for recovery and recession periods, respectively. Each period of observation was either part of an economic recovery or a recession. For the above we defined a recovery period as an increasing 12-month moving average of GDP. That is why the number of observations dropped from 111 to 98 periods in total. Standard errors in parentheses.

^{*} Levels of significance: <0.10.

^{**} Levels of significance: <0.05.

^{***} Levels of significance: <0.01.

Appendix D. Rebound effect depending on the fuel price

See Table D1.

Table D1
Rebound effect depending on the fuel price, after one year and after five years.

Fuel price [€/liter]	After one year (short-term) (%)	After five years (long-term) (%)
1.50	4.3	15.7
2.00	5.3	19.2
2.50	5.2	18.9
3.00	4.3	15.2
3.50	3.7	12.3
4.00	3.5	11.1

Appendix E. Supplementary material

Supplementary data associated with this article can be found, in the online version, at <http://dx.doi.org/10.1016/j.tra.2017.06.001>.

References

- Ajanovic, A., Haas, R., 2012. The role of efficiency improvements vs. price effects for modeling passenger car transport demand and energy demand – lessons from European countries. *Energy Policy* 41, 36–46.
- Anderson, T.W., 2003. *An Introduction to Multivariate Statistical Analysis*. Wiley, New York.
- Archibald, R., Gillingham, R., 1980. An analysis of the short-run consumer demand for gasoline using household survey data. *Rev. Econ. Stat.* 62, 622–628.
- Austin, D., Dinan, T., 2005. Clearing the air: the costs and consequences of higher CAFE standards and increased gasoline taxes. *J. Environ. Econ. Manage.* 50, 562–582.
- Bliemer, M., Rose, J., 2011. Experimental design influences on stated choice outputs: an empirical study in air travel choice. *Transp. Res. Part A* 45 (1), 63–79.
- BMWFJ, 2013. Austrian Federal Ministry of Economy, Family and Youth, Online Database of Recent Fuel Price Developments (Treibstoffpreismonitor). Available from: <<http://www.bmwjf.gv.at/ENERGIEUNDBERGBAU/ENERGIEPREISE/Seiten/Treibstoffpreismonitor.aspx>> (accessed 30/04/2013).
- Bomberg, M., Kockelman, 2007. Traveler response to the 2005 gas price spike. In: 86th Annual Meeting of the Transportation Research Board, Washington, DC.
- Brännlund, R., Nordström, J., 2004. Carbon tax simulations using a household demand model. *Eur. Econ. Rev.* 48 (2004), 211–233.
- Brög, W., 1982. The situational approach – an alternative model concept – theoretical foundations and practical applications. Paper presented at the 7th Australian Transport Research Forum, Hobart, Tasmania, Australia.
- Brög, W., Erl, E., 1983. Application of a model of individual behaviour (situational approach) to explain household activity patterns in urban area and to forecast behavioural changes. In: Carpenter, S., Jones, P. (Eds.), *Recent Advances in Travel Demand Analysis*. Gower Publishing Co., Ltd.
- Brög, W., Meyburg, A.H., Wermuth, M.J., 1983. Development of survey instruments suitable for non home activity patterns. *Transp. Res. Rec.* 944, 1–12.
- Brons, M., Nijkamp, P., Pels, E., Rietveld, P., 2008. A meta-analysis of the price elasticity of gasoline demand. A SUR approach. *Energy Econ.* 30, 2105–2122.
- Burguillo, M., Del Río, P., Romero-Jordán, D., 2017. Car use behaviour of Spanish households: differences for quartile income groups and transport policy implications. *Case Stud. Transp. Policy* 5, 150–158.
- Burke, P.J., Nishitaten, S., 2013. Gasoline prices, gasoline consumption, and new-vehicle fuel economy: evidence for a large sample of countries. *Energy Econ.* 36, 363–370.
- Castro, M., Bhat, C., Pendyala, R., Jara-Díaz, S., 2012. Accommodating multiple constraints in the multiple discrete-continuous extreme value choice model. *Transp. Res. Part B* 46 (6), 729–743.
- Chemers, M.M., 2000. Leadership research and theory: a functional integration. *Group Dynam.: Theory Res. Pract.* 4 (1), 27–43.
- Comeau, J., Chapman, D., 2002. Gasoline taxes, CAFE and the Kyoto Protocol. *Ecol. Econ.* 40, 317–320.
- Corraliza, J.A., Berenguer, J., 2000. Environmental values, beliefs, and actions: a situational approach. *Environ. Behav.* 32 (6), 832–848.
- Dagsvik, J.K., Wennemo, T., Wetterwald, D.G., Aaberge, R., 2002. Potential demand for alternative fuel vehicles. *Transp. Res. Part B* 36 (4), 361–384.
- Dahl, C.A., 2012. Measuring global gasoline and diesel price and income elasticities. *Energy Policy* 41, 2–13.
- Dargay, C., 2007. The effect of prices and income on car travel in the UK. *Transp. Res. Part A* 41, 949–960.
- de Borger, B., Mulacic, I., Rouwendal, J., 2016a. Substitution between cars within the household. *Transp. Res. Part A: Policy Pract.* 85, 135–156.
- de Borger, B., Mulacic, I., Rouwendal, J., 2016b. Measuring the rebound effect with micro data: a first difference approach. *J. Environ. Econ. Manage.* 79, 1–17.
- Dubois, B., Laurent, G., 1999. A situational approach to brand loyalty. *Adv. Consum. Res.* 26, 657–663. Environment agency Austria, 2011.
- Espino, R., de Ortúzar, J.de.D., Roman, C., 2007. Understanding suburban travel demand: flexible modelling with revealed and stated choice data. *Transp. Res. Part A* 41, 899–912.
- Frondel, M., Vance, C., 2010. Driving for fun? Comparing the effect of fuel prices on weekday and weekend fuel consumption. *Energy Econ.* 32, 102–109.
- Gillingham, K., 2010. Identifying the Elasticity of Driving: Evidence from a Gasoline Price Shock in California.
- Gillingham, K., 2012. Selection on Anticipated Driving and the Consumer Response to Changing Gasoline Prices. Yale University Working Paper.
- Gillingham, K., 2014. Rebound effects. In: Durlauf, S.N., Blume, L.E. (Eds.), *The New Palgrave Dictionary of Economics*. Palgrave Macmillan, Basingstoke.
- Gillingham, K., Rapson, D., Wagner, G., 2014. The rebound effect and energy efficiency policy. *Rev. Environ. Econ. Policy* 10 (1), 68–88.
- Gillingham, K., Iskhakov, F., Munk-nielsen, A., Rust, J., Schjerning, B., 2015. A Dynamic Model of Vehicle Ownership, Type Choice, and Usage. Unpublished Working Paper. <<http://bschjerning.com/papers/iruc.pdf>>.
- Glerum, A., Västberg, O.B., Frejinger, E., Karlstrom, A., Hugosson, M.B., Bierlaire, M., 2015. A Dynamic Discrete-continuous Choice Model of Car Ownership, Usage and Fuel Type. CIRRELET-2015-23.
- Goodwin, P.B., 1992. A review of new demand elasticities with special reference to short and long run effects of price changes. *J. Transp. Econ. Policy* 26 (2), 155–169.
- Goodwin, P., Dargay, J., Hanly, M., 2004. Elasticities of road traffic and fuel consumption with respect to price and income: a review. *Transp. Rev.* 24 (3), 275–292.
- Goulias, K.G., Brög, W., Erl, E., 1998. Perceptions in mode choice using situational approach “trip-by-trip multivariate analysis for public transportation”. *Transp. Res. Rec.* 1645, 82–93.
- Goulias, K.G., 2000. Surveys using multiple approaches. Resource Paper of workshop on multi-method and multi-instrument surveys. In: Proceedings of International Conference on Transport Survey Quality and Innovation, May 24–30, 1997, Grainau, Germany. TRB Transportation Research Circular E-C008: Transport Surveys: Raising the Standard.
- Graham, D.J., Glaister, S., 2002a. The demand for automobile fuel: a survey of elasticities. *J. Transp. Econ. Policy* 36 (1), 1–25.
- Graham, D.J., Glaister, S., 2002b. Review of Income and Price Elasticities of Demand for Road Traffic. Centre for Transportation Studies, London.
- Giuliano, G., Dargay, J., 2006. Car ownership, travel and land use: a comparison of the US and Great Britain. *Transp. Res. Part A* 40 (2006), 106–124.
- Hall, J.E., 2004. Pluralistic evaluation: a situational approach to service evaluation. *J. Nurs. Manage.* 12, 22–27.
- Havranek, T., Irsova, Z., Janda, K., 2012. Demand for gasoline is more price – inelastic than commonly thought. *Energy Econ.* 34, 201–207.
- Hensher, D.A., Rose, J.M., 2007. Bridging research and practice: a synthesis of best practices in travel demand modeling. *Transp. Res. Part A* 41 (5), 428–443.
- Herry, M., Sammer, G., 1998. *Mobilitätserhebung österreichischer Haushalte, Arbeitspaket A3-H2 im Rahmen des Österreichischen Bundesverkehrswegeplans*, Wien.
- Hess, S., Rose, J.M., 2009. Allowing for intra-responder variations in coefficients estimated on repeated choice data. *Transp. Res. Part B* 43 (6), 708–719.
- Hirota, K., Poot, J., Minato, K., 2003. Do policy incentives affect the environmental impact of private car use? Evidence from a sample of large cities. Paper prepared for the 43rd Congress of the European Regional Science Association, Jyväskylä, Finland, 27–30 August 2003.
- Hughes, J.E., Knittel, C.R., Sperling, D., 2008. Evidence of a shift in the short-run price elasticity of gasoline demand. *Energy J.* 29 (1), 93–114.
- Huntington, H.G., 2010. Short- and long-run adjustments in U.S. petroleum consumption. *Energy Econ.* 32, 63–72.
- Hymel, K.M., Small, K.A., van Dender, K., 2010. Induced demand and rebound effects in road transport. *Transp. Res. Part B* 44 (10), 1220–1241.
- Hymel, K.M., Small, K.A., 2015. The rebound effect for automobile travel: asymmetric response to price changes and novel features of the 2000s. *Energy Econ.* 49, 93–103.
- Johansson, O., Schipper, L., 1997. Measuring the long-run fuel demand of cars: separate estimations of vehicle stock, mean fuel intensity, and mean annual driving distance. *J. Transp. Econ. Policy* 31 (3), 277–292.
- Kayser, H.A., 2000. Gasoline demand and car choice: estimating gasoline demand using household information. *Energy Econ.* 22, 331–348.
- Kent, M., 2006. *Oxford Dictionary of Sports Science and Medicine*. Oxford University Press, Oxford.
- Klier, T., Linn, J., 2013. Fuel prices and new vehicle fuel economy – comparing the United States and Western Europe. *J. Environ. Econ. Manage.* 66, 280–300.
- Knittel, C., Sandler, R., 2015. The Welfare Impact of Second Best Uniform-Pigouvian Taxation: Evidence from Transportation. <http://web.mit.edu/knittel/www/papers/cobenefits_latest.pdf>.
- Kockelman, K.M., Kalmanje, S., 2005. Credit-based congestion pricing: a policy proposal and the public’s response. *Transp. Res. Part A* 39 (7), 671–690.

- Lin, C.C., Prince, L., 2013. Gasoline price volatility and the elasticity of demand for gasoline. *Energy Econ.* 38, 111–117.
- Litman, T., 2006. *Transportation Elasticities*. Victoria Transport Policy Institute, Victoria, BC, Canada.
- Mabit, S.L., Fosgerau, M., 2011. Demand for alternative-fuel vehicles when registration taxes are high. *Transp. Res. Part D* 16 (3), 225–231.
- Odeck, J., Johansen, K., 2016. Elasticities of fuel and traffic demand and the direct rebound effects: an econometric estimation in the case of Norway. *Transp. Res. Part A* 83, 1–13.
- Ortúzar, J. de D., Roncagliolo, D., Velarde, U.C., 2000. Interactions and independence in stated preference modelling. In: Ortúzar, J. de D. (Ed.), *Stated Preference Modelling Techniques*. Perspectives 4, PTRC, London.
- Ortúzar, J. de D., Willumsen, L.G., 2011. *Modelling Transport*. John Wiley & Sons, Chichester.
- Puller, S.L., Greening, L.A., 1999. Household adjustment to gasoline price change: an analysis using 9 years of US survey data. *Energy Econ.* 21, 37–52.
- Romero-Jordán, D., del Río, P., Jorge-García, M., Burguillo, M., 2010. Price and income elasticities of demand for passenger transport fuels in Spain. Implications for public policies. *Energy Policy* 38, 3898–3909.
- Schamber, L., Eisenberg, M.B., Nilan, M.S., 1990. A re-examination of relevance: toward a dynamic, situational definition. *Inf. Process. Manage.* 26 (6), 755–776.
- Sentenac-Chemin, E., 2012. Is the price effect on fuel consumption symmetric? Some evidence from an empirical study. *Energy Policy* 41, 59–65.
- Sipes, K.N., Mendelsohn, R., 2001. The effectiveness of gasoline taxation to manage air pollution. *Ecol. Econ.* 36, 299–309.
- Small, K.A., van Dender, K., 2007. Fuel efficiency and motor vehicle travel: the declining rebound effect. *Energy J.* 28 (1), 25–51.
- Sorrell, S., Dimitropoulos, J., Sommerville, M., 2009. Empirical estimates of the direct rebound effect: a review. *Energy Policy* 37, 1356–1371.
- Spissu, E., Pinjari, A., Pendyala, R., Bhat, C., 2009. A copula-based joint multinomial discrete–continuous model of vehicle type choice and miles of travel. *Transportation* 36, 403–422.
- Statistik Austria, 2010. *Statistisches Jahrbuch 2009*, Vienna, Austria.
- Statistik Austria, 2013. *Energy Balances Austria 1970 to 2012*, Vienna, Austria. Available at <http://www.statistik.at/web_en/statistics/energy_environment/energy/energy_balances/index.html>.
- Train, K., 2003. *Discrete Choice Methods with Simulation*. Cambridge University Press, Cambridge.
- Train, K., Wilson, W.W., 2008. Estimation on stated-preference experiments constructed from revealed-preference choices. *Transp. Res. Part B* 42 (3), 191–203.
- Turrentine, T.S., Kurani, K.S., 2007. Car buyers and fuel economy? *Energy Policy* 35, 1213–1223.
- Vroom, V.H., Jago, A.G., 2007. The role of the situation in leadership. *Am. Psychol.* 62 (1), 17–24.
- Wadud, Z., Graham, D.J., Noland, R.B., 2009. Modelling fuel demand for different socio-economic groups. *Appl. Energy* 86, 2740–2749.
- Wadud, Z., Graham, D.J., Noland, R.B., 2010a. Gasoline demand with heterogeneity in household responses. *Energy J.* 31 (1), 47–74.
- Wadud, Z., Noland, R.B., Graham, D.J., 2010b. A semiparametric model of household gasoline demand. *Energy Econ.* 32, 93–101.
- West, S.E., Williams, R.C., 2007. Optimal taxation and cross-price effects on labor supply: estimates of the optimal gas tax. *J. Publ. Econ.* 91, 593–617.