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The Rebound Effect in Road Transport: A Meta-analysis of Empirical Studies

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THE REBOUND EFFECT IN ROAD TRANSPORT: A META-ANALYSIS OF EMPIRICAL STUDIES - ENVIRONMENT WORKING PAPER No. 113

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ABSTRACT

The rebound effect is the phenomenon underlying the disproportionality between energy efficiency improvements and observed energy savings. This paper presents a meta-analysis of 76 primary studies and 1138 estimates of the direct rebound effect in road transport to synthesise past work and inform ongoing discussions about the determinants and magnitude of the rebound effect. The magnitude of rebound effect estimates varies with the time horizon considered. On average, the direct rebound effect is around 12% in the short run and 32% in the long run. Indirect and macroeconomic effects would come on top of these estimates. Heterogeneity in rebound effect estimates can mainly be explained by variation in the time horizon considered, the elasticity measure used and the econometric approach employed in primary studies, and by macro-level economic factors, such as real income and gasoline prices. In addition to identifying the factors responsible for the variation in rebound effect estimates, the meta-regression model developed in this paper can serve as a relevant tool to assist policy analysis in contexts where rebound effect estimates are missing.

Keywords: Rebound effect; road transport; fuel efficiency; gasoline price; meta-analysis.

JEL Classification: D12; Q41; Q48; Q58; R41; R48.

RÉSUMÉ

L'effet de rebond est un phénomène qui sous-tend la disproportionnalité entre les améliorations de l'efficacité énergétique et les économies d'énergie observées. Ce papier présente une méta-analyse de 76 études primaires et 1138 estimations de l'effet de rebond direct dans le transport routier pour synthétiser les travaux passés et informer les discussions en cours sur les déterminants et l'ampleur de l'effet de rebond. L'ampleur des estimations de l'effet de rebond varie selon l'horizon temporel considéré. En moyenne, l'effet de rebond est d'environ 12% à court terme et 32% à long terme. Les effets indirects et macroéconomiques viendront s'ajouter à ces estimations. L'hétérogénéité des estimations de l'effet de rebond s'explique principalement par la variation de l'horizon temporel considéré, la mesure d'élasticité utilisée et l'approche économétrique déployée dans les études primaires, ainsi que par des facteurs macroéconomiques tels que le revenu réel et les prix de l'essence. En plus de l'identification des facteurs responsables de la variation des estimations des effets de rebond, la méta-régression, développée dans ce papier, fournit un outil pertinent pour analyser les politiques en vigueurs dans les contextes où les estimations de l'effet rebond sont manquantes.

Mots-clés: Effet de rebond; transport routier; efficacité en carburant; prix de l’essence; méta-analyse.

Classification JEL: D12; Q41; Q48; Q58; R41; R48.

FOREWORD

This report has been authored by Alexandros Dimitropoulos, Walid Oueslati and Christina Sintek of the OECD Environment Directorate. The authors are grateful to delegates to the Working Party on Integrating Environmental and Economic Policies for helpful comments on earlier drafts of this paper. They would also like to thank Randy Chugh, Xavier D'Haultfoeuille, Gerard de Jong, David Greene, Lorna Greening, Anders Munk-Nielsen, Don Pickrell, Steve Puller, Lee Stapleton and Menglin Wang for providing additional information and estimates from their studies, Helen Beilby-Orrin and Mariano Berkenwald for clarifications on statistics on gasoline prices, Shardul Agrawala, Grégoire Garsous, and Ioannis Tikoudis for comments on previous versions of the paper, and Natasha Cline-Thomas for editorial assistance. The authors are responsible for any remaining omissions or errors. Work on this paper was conducted under the overall responsibility of Shardul Agrawala, Head of the Environment and Economy Integration Division.

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EXECUTIVE SUMMARY

Why does an increase in energy efficiency usually lead to a *less than proportional* reduction in energy consumption? The *rebound effect* is the phenomenon underlying this disproportionality between energy efficiency improvements and observed energy savings. The rebound effect is usually expressed in percentage terms, indicating how much of the expected energy savings are eventually foregone due to the increased use of the energy service. In road transport, the *direct* rebound effect implies that individuals respond to higher fuel efficiency by driving more. Such shifts in individual travel behaviour have important environmental implications, including significant increases in air and noise pollution, and entail more traffic congestion and road accidents.

The literature provides overwhelming evidence that the rebound effect exists in road transport. However, empirical estimates vary widely, ranging from negative numbers (i.e. increased fuel efficiency results in reductions of car travel) to greater than 100% (implying that improvements in fuel efficiency induce so much additional car travel that they eventually increase fuel use).

This report presents a meta-analysis of 76 empirical studies and 1138 estimates of elasticities of travel from 18 countries which can serve as possible measures of the direct rebound effect. In contrast to a narrative literature review, meta-analysis is a rigorous *statistical* approach to synthesise the findings of a narrowly defined collection of primary empirical studies. The aim of this meta-analysis is to provide a useful synthesis of past work and inform ongoing discussions about the magnitude of the rebound effect and its determinants. The meta-analysis also uses an econometric approach – formally known as meta-regression analysis – to pinpoint the sources of heterogeneity in rebound effect estimates across studies.

The magnitude of rebound effect estimates varies with the time horizon considered. Short-run estimates usually refer to drivers' responses in the first year following the fuel efficiency improvement. In contrast, long-run estimates take into account the time required by consumers to change their capital stock, i.e. to change vehicles. Estimates for the long run are found to be significantly larger than estimates for the short run. In particular, the direct rebound effect is estimated to be, on average, around 12% in the short run, whereas about 32% in the long run. Indirect and macroeconomic effects would come on top of these estimates.[1] When considering fuel efficiency standards, the long-run estimate is, in theory, the most relevant one, as households do not have the flexibility to change vehicles in the short run.

The studies analysed here provide national-level estimates of the rebound effect for 18 countries, as well as a small number of cross-country estimates. The majority of estimates concern the United States, whereas a smaller number of estimates are provided for European countries, Australia, Canada, Israel and Japan. Rebound effect estimates for China and India are also taken into consideration. The meta-analysis shows significant differences in the estimated magnitude of the rebound effect among studies and countries. Rebound effect estimates for the United States are, on average, on the low side, whereas estimates for European countries tend to be higher.

[1] Improved fuel efficiency makes private car travel cheaper and, thus, increases the income that households have available to spend elsewhere. The indirect rebound effect is caused by households' spending of this additional disposable income on goods and services whose production requires energy. If improved fuel efficiency also translates to lower costs in the production of goods and services (e.g. reduced transportation costs), and thereby to reductions of their prices, demand for these products may well increase. This implies that more energy will be used, leading to a macroeconomic rebound effect.

The meta-regression analysis reveals that cross-country differences in rebound effect estimates can be mainly attributed to differences in income and – albeit with weak statistical support – gasoline prices. Higher income (approximated here by GDP per capita) is associated with *smaller* rebound effects. The underlying reason for this relationship is that private car travel does not entail only fuel costs, but also time costs. Time costs increase with income and, thus, richer households are likely to take advantage of improved fuel efficiency to a lesser extent than less well-off ones. On the contrary, higher gasoline prices are associated with *larger* rebound effects (even though empirical evidence of this relationship is rather weak). This could be explained by two main reasons. First, higher gasoline prices are, *ceteris paribus*, associated with less intensive car use prior to the fuel efficiency improvement. Thus, even if individuals respond to improved fuel efficiency by increasing travelled distances by the same level (e.g. 1000 km per year), the increase will be higher in *percentage* terms in the country were gasoline prices are higher. Second, individuals may be tempted to increase private car travel to a larger extent (in absolute terms) in countries with high gasoline prices. Before the fuel efficiency improvement, it was cheaper to make some trips by public transport than by car. This is much more likely in countries where gasoline prices are high. After the fuel efficiency improvement, private car travel becomes more competitive and households are more likely to substitute private car for public transport for those trips. Overall, these findings highlight that caution should be exercised when assuming a certain magnitude of the rebound effect in policy analysis, as it may vary significantly across regions.

In addition to identifying the factors responsible for the variation in rebound effect estimates, the meta-regression model developed in this paper can serve as a tool to assist policy analysis in contexts where rebound effect estimates are missing. This can be especially useful in countries where it is difficult to collect data on travel demand and resources for relevant analyses are scarce. Importing data on macro-level variables which are more readily available (GDP per capita and gasoline prices), the analyst can derive estimates of potential rebound effects in such contexts. However, these estimates should be treated with caution, especially in countries with very different macroeconomic characteristics, transport infrastructure and rates of new technology adoption than the ones analysed here.

The existence of a rebound effect impacts policy significantly. Indeed, results suggest that a 10% increase in fuel efficiency would result in a 3% increase in travel demand in the long run. This induced travel partially offsets the expected energy savings from fuel efficiency improvements, in addition to contributing to mileage-related externalities, such as non-exhaust air pollution, noise, congestion and traffic accidents. Induced travel implies that even in the presence of stringent fuel efficiency standards, the implementation of price instruments is key to ensure that road transport externalities are effectively addressed. Rapid and significant improvements in fuel efficiency, along with a gradual shift towards electric transport, will also soon pose important fiscal challenges to policy makers, who will perhaps have to consider alternatives to compensate for the foregone revenues from fuel taxation. In light of these environmental and fiscal challenges, it is probably timely to reconsider the implementation of distance-based taxes, which can provide for an efficient means of addressing the externalities of car travel and ensuring the stability of an important source of fiscal revenues.[2]

[2] As the external costs of private car travel (e.g. air pollution) vary both across space and over time, distance-based taxes will be more efficient if they vary across both dimensions.

1. INTRODUCTION

Road transport is responsible for important negative externalities, including air pollution, emissions of greenhouse gases (GHG), noise, traffic congestion and road accidents. It accounted for more than 17% of global energy-related GHG emissions in 2013, and is one of the few sectors of economic activity where emissions are still increasing (OECD, 2015; Sims et al., 2014). Road transport is also one of the major sources of emissions of harmful air pollutants, such as nitrogen oxides and particulate matter, and is responsible for about half of the costs of premature deaths and health problems caused by outdoor air pollution in OECD countries (OECD, 2014). At the same time, road traffic congestion is estimated to cost humanity billions of dollars annually from time losses. In the more congested countries, these losses can equal more than 1% of GDP (OECD/ECMT, 2007). Additionally, approximately 1.24 million people died on roads in 2010, with tens of millions more suffering injuries each year (WHO, 2013).

Governments use a wide array of policy instruments to address these negative externalities, including both regulatory and market-based instruments. Motor fuel taxes are perhaps the most frequently used instrument to this end, with varying levels of stringency across OECD countries. Motor vehicle taxes, including one-off and recurrent taxes, are also used in many countries, while congestion pricing has also been introduced in a number of cities (e.g. London, Milan, Singapore and Stockholm). In addition, policy-makers frequently rely on regulatory approaches to address the external costs of road transport. Fuel efficiency standards are among the most popular regulatory instruments used to this end. To date, Brazil, Canada, China, the European Union, India, Japan, Mexico, South Korea, and the United States have either proposed or established fuel efficiency or greenhouse-gas emissions standards for vehicles. The markets of these territories comprised about 80% of global passenger vehicle sales in 2013.[3] However, GHG emissions from the transport have continued to rise since 2007, despite the increased use of more fuel efficient vehicles (Sims et al., 2014).

This report investigates an unintended consequence of fuel efficiency improvements: the *rebound effect*. The rebound, or *take-back,* effect explains why energy efficiency improvements usually lead to less than proportional reductions in energy consumption. It stems from the increased use of an energy service (in this case, travel) following an improvement in efficiency (Gillingham, Rapson and Wagner, 2015; Khazzoom, 1980). Increased efficiency of a service effectively results in a lower (per unit) service price, which can have direct and indirect effects. This study focuses only on the *direct* rebound effect, which refers to changes in efficiency and use of a particular energy service.[4] In road transport, the direct rebound effect implies that people respond to higher fuel efficiency by driving more.

The rebound effect is at the core of the debate on the relative efficacy of fuel efficiency standards in comparison with market-based instruments. Although fuel efficiency standards are often established with similar end-goals as price instruments, the intermediate effects of the two policy approaches may, in fact, be the opposite. For example, a motor fuel tax increases the cost of driving per unit of travel, thereby

[3] *www.theicct.org*.

[4] One can also consider the *indirect* rebound effect, where a change in the price of an energy service results in changes in the demand for other goods and services (Sorrell and Dimitropoulos, 2008). For a more general typology of rebound effect definitions, see Gillingham, Rapson and Wagner (2015).

reducing travel demand. Inversely, improved fuel efficiency decreases the cost of driving per unit of travel, which may therefore result in an increase in driving, a phenomenon called *induced travel*. [5]

Induced travel from improvements in fuel efficiency has important policy implications. First, induced travel partially offsets the expected energy savings from an increase in fuel efficiency. In addition, induced travel contributes to mileage-related externalities, such as higher levels of non-exhaust air pollution, noise, congestion and traffic accidents (see also van Dender and Crist, 2011). Thus, the rebound effect plays an important role in the choice of the appropriate policy instrument, or combination of instruments, to address road transport externalities.

Earlier literature has shown that considering the change in travel demand from an *increase in fuel efficiency* is probably the most straightforward measure of the direct rebound effect in road transport (see e.g. Frondel, Peters and Vance, 2008; Sorrell and Dimitropoulos, 2008). However, a far more popular measure used in the literature is the change in travel induced by a *reduction in the cost of driving per distance unit* (kilometre or mile). Many empirical studies also resort on changes in travel from a *reduction in (retail) fuel prices* to estimate the rebound effect in road transport. The last approach is usually followed due to difficulties in finding reliable data on fuel efficiency or due to econometric concerns (Frondel, Ritter and Vance, 2012).

Although there is a general consensus in the literature that the rebound effect exists in road transport, empirical estimates vary widely, ranging from essentially zero (no induced travel) to greater than 100% (implying that improvements in fuel efficiency increase fuel consumption – a phenomenon often denoted as “backfire”). Indeed, Gillingham, Rapson and Wagner (2015) note that estimates of the rebound effect “show incredible variation”, most likely caused by “its varying definitions, as well as variation in the quality of data and empirical methodologies used to estimate it”. A phenomenon first suggested by Jevons (1865), then revisited by Khazzoom (1980), the rebound effect is once again receiving attention due to increasing concerns over environmental problems. However, the literature still suffers from a lack of clear-cut definitions and guidelines for measurement, sometimes even leading to significantly different estimates of the rebound effect obtained from the same data source (Gavankar and Geyer, 2010).

This report presents a meta-analysis of 76 primary studies measuring the direct rebound effect in road transport in order to provide a useful synthesis of past work. The scope of the analysis is narrowed as much as possible to passenger transport, as this project focuses on individual behaviour. Meta-regression analysis provides insights into cross-country differences in the magnitude of the rebound effect by considering factors such as differences in income and real gasoline prices.

The rest of the report is structured as follows. Section 2 provides background on theoretical and empirical literature related to the rebound effect. Section 3 briefly explains why a meta-analysis is a rigorous and effective method to synthesise past empirical literature on the rebound effect in road transport. Section 4 provides a statistical summary of the collected empirical estimates, while Section 5 presents the results of the meta-regression analysis. Section 6 concludes and discusses policy implications.

[5] The term *induced travel* is used here to denote increases in travel demand stemming from improvements in fuel efficiency. In other contexts, the term is used to denote induced travel from road capacity expansions (cf. e.g. Cervero and Hansen; Hymel, Small and van Dender, 2010).

2. BACKGROUND

As stated by Sorrell and Dimitropoulos (2008), “the rebound effect results in part from an increased consumption of energy services following an improvement in the technical efficiency of delivering those services”. In the context of road transport, this technical efficiency can be quantified in different ways. In some OECD countries, including Chile, Japan, Korea, the United States and the United Kingdom, efficiency is measured by *fuel economy*, defined as the ratio of the distance travelled to the amount of fuel consumed by the vehicle (e.g. miles per gallon, kilometres per litre). In most OECD countries, however, efficiency is measured by the inverse of this ratio, often termed *fuel consumption* or fuel intensity (e.g. litres per 100 kilometres) (see also Harding, 2014).

The empirical literature on the rebound effect largely focuses on fuel economy, as it provides a more direct measure of the amount of energy input required to maintain a specific level of an energy service. Therefore, the terms fuel efficiency and fuel economy will henceforth be used interchangeably. It holds that $e=t/f$, where e is fuel efficiency, t is the distance travelled (in kilometres or miles) and f is the amount of fuel consumed (in litres or gallons).

In the realm of economics, the rebound effect is empirically measured as an elasticity of demand. It can be shown that $E_e^f = E_e^t - 1$, where E_e^f is the elasticity of *fuel demand* with respect to energy efficiency and E_e^t is the elasticity of *travel demand* with respect to fuel efficiency (Sorrell and Dimitropoulos, 2008). If E_e^t is greater than zero, E_e^f is lower in absolute terms than unity, implying that an increase in fuel efficiency will lead to a less than proportional reduction in fuel demand. In fact, the *elasticity of travel demand with respect to fuel efficiency* reflects exactly the deviation of this reduction from proportionality and can, therefore, serve as a straightforward measure of the rebound effect in road transport (see also Greene, Kahn and Gibson, 1999; Hymel, Small and van Dender, 2010; Wheaton, 1982). Thus, the first measure of the rebound effect can be written as:

$$R_1 = E_e^t = \frac{\partial t}{\partial e}\frac{e}{t}\,. \tag{1}$$

Considering, however, c as fuel cost per unit of travel (e.g. mile) and p as fuel price, the identity $c = p/e$ holds (Small and Van Dender, 2007). Earlier literature has shown that if fuel prices are exogenous, and responses to fuel efficiency improvements are symmetric to responses to fuel price reductions, the elasticity of travel demand with respect to fuel efficiency is equal to the negative of the *elasticity of travel demand with respect to fuel cost per unit of travel*, E_c^t. This leads to an alternative measure of the rebound effect:

$$R_2 = -E_c^t = -\frac{\partial t}{\partial c}\frac{c}{t}\ . \tag{2}$$

As mentioned above, the intermediate effect of an improvement in fuel efficiency is to decrease the fuel cost of driving per unit of travel. Therefore, the elasticity with respect to this cost is often used to empirically measure the rebound effect, although perhaps in a less direct way than the elasticity with respect to fuel efficiency (see, for example, Greene, 1992; Jones, 1993; Small and Van Dender, 2007).

In addition, data on fuel efficiency is often less abundant, harder to measure, or lacking in variation. This leads authors to exploit more readily available data on fuel prices. This has resulted in a third measure of the rebound effect (see, for example, Frondel and Vance, 2014; Greene, Kahn and Gibson, 1999; Munk-Nielsen, 2014): *the negative of the elasticity of travel demand with respect to fuel price*, E_p^t:

$$R_3 = -E_p^t = -\frac{\partial t}{\partial p}\frac{p}{t}. \tag{3}$$

For one to consider that these three elasticities are just different measures of the same underlying phenomenon, a certain set of assumptions must be made.[6] For the elasticity with respect to fuel costs, one must assume that fuel efficiency is insensitive to changes in fuel price, i.e. that the elasticity of fuel efficiency with respect to fuel price is zero. Similarly, estimates of the rebound effect based on the elasticity with respect to fuel price often assume that fuel efficiency is held constant. Still, if empirical interest lies with the effect of changes in fuel efficiency, this may seem counterintuitive. Indeed, using the elasticity with respect to fuel price as a direct measure of the rebound effect also rests on the assumption of an equal but opposite response of travel to changes in fuel efficiency and changes in fuel price. However, there is no consensus about the validity of this assumption in the literature (see, for example, Frondel, Ritter and Vance, 2012; Hymel and Small, 2015; Linn, 2016).

A fourth elasticity suggested by the literature as a possible measure of the rebound effect is the elasticity of *fuel consumption* with respect to fuel price. This measure does not fall within the scope of this meta-analysis, as the focus here is on elasticities of travel demand. A number of comprehensive reviews and meta-analyses have already focused on the elasticity of fuel consumption with respect to fuel price (see Box 1). However, few attempts have been made to review elasticities of travel demand with a view to provide insights into the magnitude of the rebound effect (see Sorrell, Dimitropoulos and Sommerville, 2009; Hanly, Dargay and Goodwin, 2002) and those attempts date back to a time when the number of relevant estimates did not allow the conduct of a meta-analysis of the aforementioned travel demand elasticities. This meta-analysis wishes to fill this gap in empirical literature and, thus, focuses on the effects of fuel efficiency changes on *travel* demand.

One of the most influential studies in the rebound effect literature is Small and van Dender (2007), which uses the elasticity of vehicle miles travelled (VMT) with respect to fuel cost per mile as the measure of the rebound effect. Their approach considers that VMT, number of vehicles, and fuel efficiency are simultaneously determined. This accounts for endogenous changes in fuel efficiency, and therefore likely provides a reliable estimate of the rebound effect. Until Small and van Dender (2007), many papers estimating the rebound effect relied on ordinary least squares (OLS). This could be problematic because fuel efficiency is very likely dependent on fuel price. If this dependency is not taken into account, it may result in biased estimates of the rebound effect, particularly for estimates based on the elasticity with respect to fuel cost per unit of travel. Indeed, Small and van Dender note that one of their innovations comes from the ability to postulate an *exogenous* change in fuel efficiency. Estimates of the rebound effect based on variation in fuel prices make it "implausible that [fuel efficiency] is exogenous".

[6] While the elasticities of travel with respect to cost (2) and fuel price (3) are expected to be negative, the elasticity with respect to fuel efficiency (1) should, theoretically, be positive.

Box 1. Meta-analyses and reviews of the price elasticity of fuel demand

Espey (1998) focuses on price and income elasticities of gasoline demand, concluding that the price elasticity appears to be increasing over time. The author conducts a meta-analysis using functional form, lag structure, time-span, national setting, and estimation technique as control variables. She finds that using static versus dynamic models affects the magnitude of the elasticities in both the short and long run. The author also notes considerable variation across countries, particularly in the short run.

Brons et al. (2008) conduct a meta-analysis of the price elasticity of gasoline demand using a Seemingly Unrelated Regression (SUR) approach with cross-equation restrictions, leading to more precise results. Using this approach, they are able to utilise gasoline demand elasticity estimates with respect to fuel efficiency, travel demand, car ownership and gasoline price. Like Espey (1998), they find that the geographical area, the year of the study, the data type, the time horizon and the functional specification of the primary study significantly impact estimates of the price elasticity of gasoline demand. From their SUR approach, they are able to identify that the change in gasoline demand following a price change is mainly driven by changes in fuel efficiency and travel demand.

Hanly, Dargay and Goodwin (2002) conduct a literature review of 69 studies from the UK or "other countries broadly comparable to the UK". Their survey includes price and income elasticities for traffic, vehicle stock, and fuel consumption. They find that, on average, long-run estimates of the price elasticity of fuel demand are much larger than short-run estimates. Among static estimates, they note significant differences between estimates derived from cross-sectional, panel, and time-series data, with cross-sectional data producing the largest elasticity on average. They also note that the elasticity of aggregate fuel consumption differs significantly from fuel consumption per vehicle; estimates using aggregated data tend to be much larger on average.

Graham and Glaister (2002) also focus on the demand for fuel, but include elasticities from many different countries. Again, one of the most significant differences in estimates comes from long-run versus short-run elasticities, with long-run estimates falling in the -0.6 to -0.8 range while short run estimates being closer to -0.2 to -0.3. They also note significant variation in price elasticity estimates of gasoline demand between OECD countries.

Related to the idea of exogeneity of fuel efficiency, Gillingham, Rapson and Wagner (2015) underline the role of changing costs from improved energy efficiency. If energy efficiency increases in response to policy standards, then it is likely that this efficiency increase will be costly, since it is not the result of a pure technical innovation. This may increase the price of the energy service, or even change other characteristics about the service. For example, it is possible that more fuel efficient cars – such as hybrids or diesel cars – have consistently higher purchase prices than their less fuel efficient counterparts. Similarly, it could be that more fuel efficient cars tend to have less desirable characteristics from the consumer's point of view, such as being smaller and less comfortable, having less horsepower, or lower safety ratings. These changing costs may therefore have an impact on the magnitude of the rebound effect.

The potential impact of changing capital costs is discussed in West et al. (2015). The authors consider the state of Texas during the Cash for Clunkers programme in 2009 and conclude that households did not drive more after purchasing more fuel efficient cars – a rebound effect equal to zero. This result comes from the inclusion of a term called *attribute-based adjustment* in their model, in addition to the standard rebound effect (estimated as the elasticity of vehicle miles travelled with respect to fuel cost per mile). Their reasoning for including this second term is to capture changes in vehicle characteristics conditional on the price-per-mile of driving. They find that improved fuel efficiency is negatively correlated with a variety of vehicle characteristics that are complementary to driving, including spaciousness, safety, and horsepower. As a result, purchasing a car with less desirable attributes causes the demand curve for VMT to shift in, essentially cancelling out the increase in VMT from the rebound effect. Therefore, there is no change in overall travel demand.

It is possible, however, that this is not always the case. For example, diesel cars tend to be more fuel efficient (despite being more polluting) than their gasoline counterparts, often without significant change in other vehicle attributes of primary importance to consumers (e.g. safety, reliability, comfort, performance). Similarly, in recent years, much progress has been made in the design of hybrid cars; today, many car manufacturers offer the same model in both gasoline and hybrid variants, with few – sometimes hardly noticeable – physical or aesthetic differences between the two. In this case, switching to a more fuel efficient vehicle may not necessarily result in a decreased demand for travel. This seems to be an area where further research may prove insightful.

Several narrative reviews of the rebound effect in passenger vehicle transport have been completed. Greening, Greene and Difiglio (2000) survey the relevant literature from the United States and conclude that the magnitude of the rebound effect is "very low to moderate". However, their survey considers the rebound effect in a number of different sectors, as well as indirect and economy-wide effects, instead of focusing more in detail on the direct rebound effect in road transport, as done here. In addition, they largely review empirical analyses using data from the 1970s and 1980s, or even earlier. However, a large number of studies have been completed since the publication of this survey, using more recent data. Given that both economic and environmental conditions have changed considerably over the past several decades, it may be that the conclusions from Greening, Greene and Difiglio (2000) are no longer valid, particularly as the theoretical understanding of the rebound effect and econometric techniques have advanced.

Other relevant papers include parallel blind studies from Goodwin, Dargay and Hanly (2004) and Graham and Glaister (2004), which provide surveys of various elasticities related to fuel and travel demand. Although their focus is not strictly on the rebound effect itself, they both review estimates of the elasticity of travel demand with respect to fuel price. Goodwin, Dargay and Hanly (2004) find significant differences in estimates between dynamic versus static regression models, as well as some differences between estimates using aggregate versus vehicle-level data. They summarise that, on average, the elasticity of travel demand with respect to fuel price is about -0.1 in the short-run and -0.3 in the long-run when the model is dynamic. When the model is static, however, average estimates range from -0.27 to -0.69 depending on the type of data and level of aggregation used. Similarly, Graham and Glaister (2004) find average estimates of elasticities ranging from -0.16 to -0.5, depending on data type and short-run versus long-run estimates.

These existing surveys and analyses help provide a starting point for this meta-analysis. Yet, there are some systematic differences in the existing literature between studies that use distinct measures of the rebound effect. Studies estimating the rebound effect based on fuel efficiency tend to use micro-level data; that is, they consider individual or household travel rather than aggregated travel. For studies using cross-sectional data, authors exploit variation in fuel efficiency between individual vehicles. Authors in this camp usually take published or on-road "corrected" fuel efficiency ratings for each vehicle, or an average rating for a household with multiple vehicles. For panel studies considering households or individuals over time, authors often calculate fuel efficiency using available data on travel, gasoline purchases, and gasoline prices in order to have variation in the key explanatory variable. It is interesting to note that many studies estimating the rebound effect based on fuel efficiency include current fuel price as a control variable, sometimes providing a way to compare the magnitude of the estimates of the elasticity with respect to fuel efficiency with the magnitude of the ones of the elasticity with respect to fuel price.

Importantly, relatively few studies using the elasticity with respect to fuel efficiency treat fuel efficiency as endogenous. Several studies on the aggregate level test and find that they cannot reject the exogeneity of fuel efficiency. Indeed, Greene (2012) notes that "national time series data do not indicate that vehicle travel, vehicle stock and fuel cost per mile are simultaneously determined". These results are consistent with those of Schimek (1996). However, other studies, particularly on the micro-level, simply do not consider the endogeneity of fuel efficiency, which may result in bias.

Given the rather lengthy history of the rebound effect literature and the variety of econometric approaches, studies considering elasticity with respect to fuel cost per unit of travel are relatively diverse. Many focus the analysis on a micro-level, considering panel data on a household or vehicle level. However, equally as many consider countries or regions, utilising aggregated time series or panel data. The key independent variable of interest is almost always calculated by the authors, combining data on fuel prices, fuel demand, and travel demand. Alternatively, authors using aggregated data can calculate fuel costs per unit of travel using the average fleet fuel efficiency and fuel prices. However, studies using aggregate data on travel demand often note the possible caveat of significant measurement error. This is the case particularly in the US data on vehicle miles travelled, as they are generally reported independently by each state, and often different states have different methodologies for measurement and aggregation.

As with the elasticity with respect to fuel costs, there is much diversity among studies estimating the rebound effect from the elasticity with respect to fuel price. There is a mix of studies using aggregate and micro-level data. Studies explicitly estimating the elasticity of travel demand with respect to fuel prices tend to use time series or panel data in order to utilise variation in fuel prices over time. However, when current fuel price is simply included as a control in a regression where fuel efficiency is the variable of interest, studies tend to use cross-sectional data. Standard deviation is the largest among estimates of the elasticity with respect to fuel price, partially reflecting the large heterogeneity in the use of fuel price in relevant empirical models.

As mentioned, using the elasticity with respect to fuel cost per unit of travel either requires special care in the treatment of endogeneity of fuel efficiency, or rests on the same assumption of symmetric consumer response to changes in fuel price and efficiency. Additionally, using the elasticity with respect to fuel price as a measure of the rebound effect directly assumes that consumers respond symmetrically to changes in fuel price and changes in fuel efficiency, which may not necessarily be the case. About this question alone there exists conflicting evidence within the literature.

Some papers (e.g. Frondel, Peters and Vance, 2008; Frondel and Vance, 2014) find no statistical difference between any of the above elasticities, indicating that any definition provides a valid estimate of the rebound effect. Greene, Kahn and Gibson (1999) conclude that the "data generally did not contradict the hypothesis that consumers respond symmetrically to proportionate changes in fuel price or [fuel efficiency]". However, others (e.g. Greene, 2012; Hymel and Small, 2015) find that reductions in fuel price have a much larger impact on travel demand than increases in fuel efficiency. On the other hand, Linn (2016) finds the opposite: the estimated coefficient on fuel economy is systematically much larger in absolute terms than that of fuel price. If it is the case that consumers do not respond the same to changes in fuel price as to changes in fuel efficiency, this may invalidate the use of the elasticities with respect to fuel costs per unit and fuel price as direct measures of the rebound effect.

Additionally, consumer responses to changes in fuel efficiency versus fuel costs are important for policy. If the magnitudes are equal, then it could be possible to use fuel taxes in conjunction with higher fuel efficiency standards to offset any induced travel. A higher cost of fuel would help to discourage the increased demand for travel from higher fuel efficiency. However, if, for example, travel demand in response to changes in fuel efficiency is much larger than the response to fuel price changes, then this could provide evidence of the inefficacy of fuel efficiency standards in reducing private car travel. In the latter case, policy-makers may then prefer to use fuel taxes or other price instruments over fuel efficiency standards in order to reduce car travel and consequently road transport emissions.

3. META-ANALYSIS

Given the diverse and extensive background of the rebound effect, this report presents a meta-analysis of empirical estimates of the rebound effect in road transportation. Meta-analysis is a rigorous statistical approach to synthesise the findings of a narrowly defined collection of primary empirical studies (Glass, 1976). It is one of the main research methods used in medicine and it is becoming increasingly widespread in economics and other social sciences (see Box 2). Generally, there are at least three main goals of a meta-analysis. First, to estimate the true effect size (i.e. the magnitude of the rebound effect); second, to understand why there is heterogeneity in estimates of the effect size across studies; and third, to provide an empirical framework suitable for making predictions of the effect of interest in other contexts (Nelson and Kennedy, 2009). A meta-analysis allows for the systematic review of heterogeneous results from a large number of studies to produce a useful and coherent synthesis of past work. This is, to the best of our knowledge, the first meta-analysis conducted on the rebound effect – in terms of change in *travel* – in road transport.

The next section (Section 4) presents descriptive and summary statistics of rebound effect estimates. This analysis synthesises the abundant and heterogeneous information in the literature. This step is followed by the meta-regression analysis, the results of which are reported in Section 5. The meta-regression analysis focuses on disentangling the determinants of heterogeneity in rebound effect estimates. The econometric models constructed for the meta-regression analysis investigate how: (i) differences in primary study design and methodology and (ii) differences in time- and country-specific factors (real gasoline prices and GDP per capita) influence rebound effect estimates.

Three main statistical challenges arise when conducting a meta-analysis (Nelson and Kennedy, 2009). First, there is likely sample heterogeneity. Heterogeneity in primary studies and rebound effect estimates can be controlled for using variables capturing differences in the design and methodology of the study. Second, there is often heteroskedasticity of effect-size variances, which can be dealt with by weighting each primary estimate by the inverse of its variance to give more reliable estimates greater weight.[7] Third, correlation within and between primary studies can be problematic. In this meta-analysis, more than 1138 estimates of the rebound effect come from 76 papers. This means that each primary study offers multiple estimates (almost 15 on average), which may well be correlated. In addition, estimates could be correlated across papers with the same authors, or even studies with different authors but which use the same data source (which is often the case for US estimates). There are many techniques which can be used to treat this problem. One possible solution is to take only one estimate from each paper. However, this is often undesirable due to the resulting small sample size and the, usually arbitrary, nature of the criteria used to arrive at a preferred estimate per study. Another way to address this problem is to test the robustness of the findings using a variety of econometric methods, ranging from generalised least squares to panel data techniques. This meta-analysis follows the second approach to address concerns over correlation among estimates.

[7] In the case of missing standard errors, it may be useful to proxy the variance using the sample size of the primary study (see e.g. Nelson and Kennedy, 2009).

Box 2. Meta-analysis

Perhaps the first meta-analysis was conducted by British statistician Karl Pearson in 1904, although the name "meta-analysis" itself did not yet exist (O'Rourke, 2006). Pearson analysed data related to typhoid fever vaccination and infection rates, combining observations from several different clinical studies. Few meta-analyses were conducted in the following decades, and the studies that used the technique were largely confined to the medical field (e.g. Daniels and Hill, 1952; Park et al.,1928). However, by the 1970s, researchers in many different fields were overwhelmed by the number of existing studies, and, thus, began looking into methods that would help them understand the mass of results (O'Rourke, 2006). Therefore, statisticians turned to the meta-analysis as a quantitative method to rigorously compare and synthesise heterogeneous findings from separate sources. In 1976, Gene Glass first coined the term meta-analysis and formally defined it as "the statistical analysis of a large collection of analysis results from individual studies for the purpose of integrating the findings" (Glass, 1976). The method was developed and fine-tuned for economic research in subsequent decades, giving way to meta-regression analysis, which performs a regression analysis on the empirical results of existing regression analyses (see, for example, Stanley and Jarrell, 1989; Weitzman and Kruse, 1990).

Instead of the traditional literature review or narrative survey in economics, meta-regression analysis serves as a quantitative approach to synthesise existing empirical research. The process begins with collecting existing empirical primary studies that measure a comparable outcome, such as an elasticity, a willingness-to-pay, or a value of a statistical life. In the meta-regression, this outcome – called the effect size – serves as the dependent variable, with each effect size as one observation. The attributes of each primary study (e.g. model specification, econometric technique, data source) serve as the explanatory variables, usually in the form of dummy variables. Additionally, using primary study attributes as controls can identify the effects of using different methodologies or data on the effect size. This helps to explain some of the variation in effect sizes between different studies (Nelson and Kennedy, 2009).

One of the concerns often raised when conducting a meta-analysis is a phenomenon known as *publication bias*. Publication bias signifies the idea that journals tend to favour statistically and economically significant results which are consistent with economic theory (Stanley and Jarrell, 1989; Stanley and Doucouliagos, 2012, pp. 51-79). This implies that a meta-analysis which relies only on studies published in academic journals is likely to overestimate the magnitude of the effect of interest. A first step towards addressing the potential issue of publication bias is to collect estimates from unpublished sources, such as discussion papers, manuscripts, or conference presentations (Nelson and Kennedy, 2009). About one-sixth of the estimates used in this meta-analysis are derived from unpublished sources.

4. STATISTICAL ANALYSIS

In general, it is crucial for a meta-analysis to be as wide-reaching and inclusive as possible in the collection of primary studies in order to strengthen the robustness of the regression results and avoid potential biases. Therefore, this meta-analysis aimed to collect as many studies of the rebound effect in passenger transport as possible, including articles published in academic journals and books, unpublished working papers, discussion papers, conference presentations, and policy reports.

As a starting point, widely cited papers, prior narrative reviews and surveys of existing literature were consulted; this allowed identification of other important works on the topic. This step was followed by an online database search of ScienceDirect, EconLit, Wiley, IngentaConnect, Google Scholar, JSTOR, and NBER, as well as a detailed search for unpublished conference papers from relevant associations of economists (AERE, EAERE, IAEE, ITEA). Additionally, a search of relevant policy reports was made in the websites of ministries of environment, energy, and transport and environmental protection agencies of some OECD countries. Individual researchers and national experts were also contacted on an ad hoc basis to widen the scope of the search.

Initially, more than 100 studies were collected. However, in order to be included in this meta-analysis, studies must perform an econometric analysis to estimate one of the elasticities presented in Section 2. Studies focusing on freight transport were not further considered, as elasticities in the commercial sector are influenced by different factors from the ones affecting elasticities in passenger transport. In the end, the database constructed by the authors of this report contains 1160 estimates from 76 studies. The highest and lowest 1% of these estimates were not included in the empirical analysis that follows, as their magnitude was considered implausible. The complete list of studies used in the analysis can be found in Table A.1 in Appendix A.

Table 1 summarises the estimates by elasticity measure and country. A number of observations can be drawn from this table. First, estimates of the rebound effect in road transport are concentrated on a relatively small number of countries; nationwide estimates are only provided for 16 OECD countries, People's Republic of China and India. Second, estimates of the rebound effect based on the elasticity with respect to fuel efficiency are much scarcer than estimates of the elasticity of travel with respect to fuel costs or price. Third, regardless of the measure used, there is significant heterogeneity in estimates among studies and countries. It is important to note that Table 1 does not reveal whether estimates vary due to differences in the country of focus or differences in the design and methodology of primary studies. The meta-regression analysis presented in Section 5 provides a much clearer picture of the extent to which the identified differences can actually be attributed to country or study characteristics.

Summary statistics of rebound effect estimates by elasticity measure and primary study are presented in Tables A.2 to A.4 in the Appendix. The Tables also present the country and time period on which estimates are based. Some studies produce estimates of the rebound effect based on more than one elasticity measure or for more than one country.

Figure 1 depicts the distribution of estimates of the rebound effect, while Table 2 presents summary statistics by elasticity measure and for all measures combined. Figure 1 shows that the distribution is skewed to the right. The unweighted means presented in Table 2 (see third column) reveal that the rebound effect is, on average, in the area of 24%.[8] Estimates based on the elasticity of travel with respect to fuel costs are slightly lower (about 20%), whereas estimates relying on the elasticity of travel with respect to fuel efficiency and fuel price are slightly higher, 27% and 26% respectively. However, the relatively high standard deviation of rebound effect estimates unveils considerable heterogeneity, even among estimates using the same elasticity measure. While unweighted statistics may provide a general idea of the magnitude of the rebound effect, they should be interpreted with great caution. In particular, they neither account for the number of estimates derived per primary study nor for the precision with which effects are estimated. Thus, they are prone to overweighting studies which provide more estimates and effects which are less precise.

[8] Note that Tables and Figures present estimates in *proportions*, whereas the interpretation of the results is made in *percentage* terms, as is common in the literature on the rebound effect. For example, the 24% figure mentioned here corresponds to the 0.236 figure presented in Table 2.

Table 1. Estimates of the rebound effect by elasticity measure and country

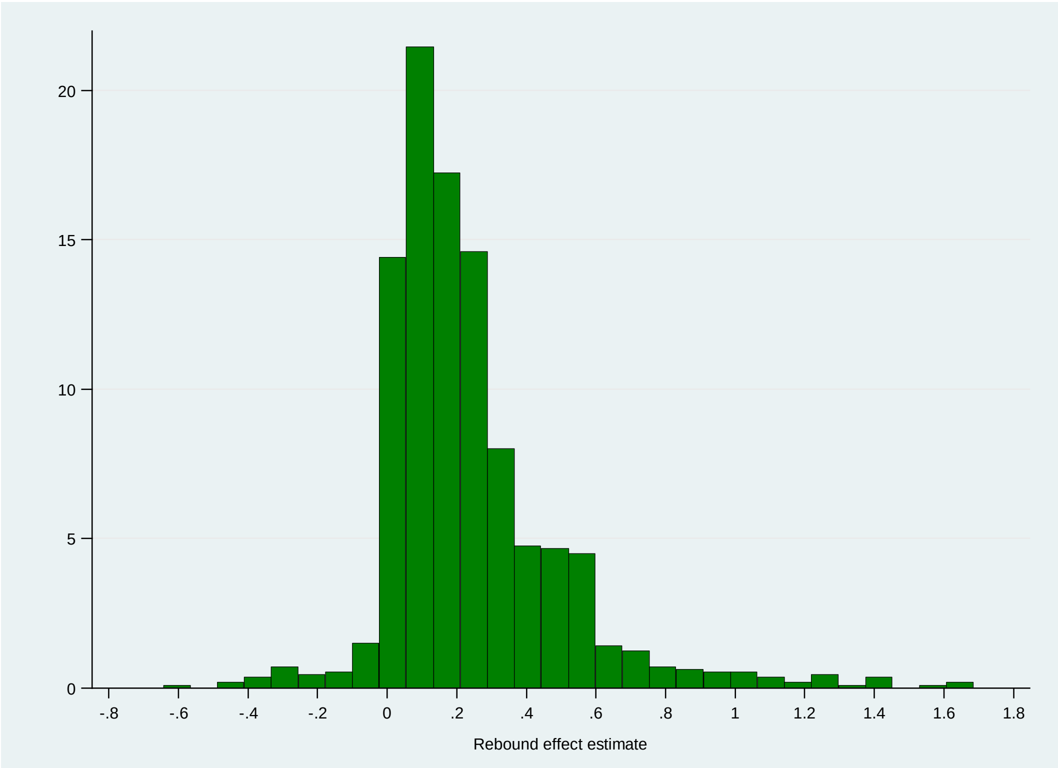
Country	No. of studies	No. of Estimates	Unweighted mean	Std Deviation
Panel A: Elasticity w.r.t fuel efficiency				
China	1	20	0.724	0.458
Denmark	3	18	0.128	0.160
Germany	5	14	0.574	0.285
Israel	1	3	0.355	0.207
Japan	2	24	0.231	0.249
Switzerland	1	4	0.528	0.301
United Kingdom	1	24	-0.134	0.267
United States	10	97	0.252	0.189
Cross-national	1	3	0.074	0.025
Total #	24	207	0.266	0.330
Panel B: Elasticity w.r.t fuel costs				
Australia	2	14	0.240	0.107
Austria	1	2	0.155	0.049
Canada	2	13	0.173	0.132
Denmark	3	11	0.404	0.172
France	3	5	0.456	0.284
Germany	4	9	0.509	0.113
India	1	2	0.800	0.184
Italy	1	2	0.405	0.219
Netherlands	2	2	0.770	0.636
Sweden	1	2	0.145	0.134
United Kingdom	2	44	0.170	0.206
United States	24	313	0.169	0.168
Cross-national	3	12	0.241	0.159
Total #	43	431	0.197	0.193

Table 1. Estimates of the rebound effect by elasticity measure and country (cont.)

Country	No. of studies	No. of Estimates	Unweighted mean	Std Deviation
Panel C: Elasticity w.r.t fuel price				
Denmark	3	66	0.398	0.199
France	3	18	0.150	0.066
Germany	7	38	0.534	0.234
Israel	1	1	0.661	n.a.
Norway	2	6	0.203	0.098
Spain	1	18	0.287	0.201
United Kingdom	1	31	0.130	0.185
United States	25	319	0.210	0.256
Cross-national	1	3	0.529	0.026
Total	44	500	0.258	0.259

Note: Studies based on individual US states (California, Pennsylvania) are merged with nationwide estimates.
[#] Total number of studies does not equal the sum of studies per country, as some studies provide estimates for multiple countries.

Figure 1. Distribution of estimates of the rebound effect



Note: The figure is based on 1138 estimates from primary studies.

Therefore, it is also important to consider weighted averages. In doing so, it is not only necessary to take into account the correlation between estimates stemming from the same study, but also the correlation between estimates from similar studies. Two studies are considered to be similar, if they draw on (broadly) the same dataset – or an extended or updated version of it – and they share at least one co-author. Considering this measure of similarity, 60 groups of studies are constructed.[9]

Two weighting schemes are employed to this end. Weighting scheme A divides each estimate by the number of estimates produced by the group of primary studies. This is to ensure that no study exerts undue influence over the results. Weighting scheme B further multiplies each estimate by the sample size with which it was estimated.[10] This is to take into account that, *ceteris paribus*, studies with a larger sample size tend to produce more precise results.[11] Weighting each estimate by a measure of its precision also helps to deal with the issue of heteroskedasticity mentioned in the previous section (Nelson and Kennedy, 2009).

Statistics based on weighting scheme A are noticeably different from the ones of the unweighted case. The relationship between elasticities with respect to fuel efficiency and fuel costs is reversed, with the former being around 21% and the latter reaching 30%. When also accounting for differences in the precision with which estimates are produced (weighting scheme B), the average rebound effect is much lower, regardless of the elasticity measure used. This implies that studies with lower sample sizes tend to overestimate the rebound effect. The divergence between unweighted and weighted estimates (scheme B) is particularly acute when focusing on the elasticity with respect to fuel efficiency. The weighted estimate is 6.4%, less than a quarter of the unweighted one (27%). However, this may be due to the relatively strong influence of estimates stemming from Danish micro-data on the weighted average, which are not necessarily representative of the situation in other countries. Average estimates of the other two rebound effect measures are significantly higher than estimates of the elasticity with respect to fuel efficiency.

[9] The studies grouped together are the following: (I) Ajanovic and Haas (2012); Ajanovic, Schipper and Haas (2012); (II) Frondel, Martinez Flores and Vance (2016); Frondel, Peters and Vance (2008); Frondel, Ritter and Vance (2012); Frondel and Vance (2009, 2011, 2013); (III) Greene (1992, 2012) and Jones (1993) – which extends the work of Greene (1992); (IV) Hymel and Small (2015); Hymel, Small and van Dender (2010); Small and van Dender (2007); (V) Gillingham and Munk-Nielsen (2015), Gillingham et al. (2015), Munk-Nielsen (2015); (VI) Hensher, Milthorp and Smith (1990) and Hensher and Smith (1986); (VII) Mannering (1983, 1986) and Mannering and Winston (1985); and (VIII) Su (2012, 2015).

[10] The weights used in scheme B can thus be written as: $w_B = s/N$, where s is the sample size used for the estimation of the effect in the primary study and N is the number of estimates derived from the group of studies. In the few instances where a study produces estimates for different countries, N is equal to the number of estimates derived per country in the group of primary studies.

[11] Typically, the preferred measure of precision is the standard error of each estimate. However, in this meta-analysis, the standard error was not provided and could not be recovered for a significant portion of the estimates. Following standard practice in the field (see e.g. Nelson and Kennedy, 2009), each estimate was instead weighted by the sample size used in the primary study.

Table 2. Summary statistics of empirical estimates of the rebound effect in road transport

		Unweighted			Weighted A			Weighted B		
Rebound effect definition	Observations	Mean	Median	Std. deviation	Mean	Median	Std. deviation	Mean	Median	Std. deviation
All	1138	0.236	0.174	0.253	0.278	0.210	0.274	0.196	0.150	0.150
Elasticity w.r.t. fuel efficiency	207	0.266	0.245	0.330	0.209	0.161	0.289	0.064	0.023	0.163
Elasticity w.r.t. fuel costs	431	0.197	0.150	0.193	0.298	0.221	0.269	0.140	0.097	0.113
Elasticity w.r.t. fuel price	500	0.258	0.187	0.259	0.276	0.200	0.281	0.218	0.192	0.168

Note: For elasticities with respect to fuel costs and fuel price, the table presents the negative of the estimates derived from the primary study. Weighted statistics A are calculated on the basis of the inverse of the number of estimates per group of studies. Weighted statistics B are calculated on the basis of the product of the inverse of the number of estimates per group of studies and the sample size used to estimate them.

Average estimates are informative, but they do not provide insights into the determinants of heterogeneity in rebound effect estimates. The meta-regression analysis that follows in the next section focuses on unravelling these sources of heterogeneity, but it is useful to draw an important distinction between short- and long-run estimates at this point. Short-run estimates usually stem from dynamic models and refer to drivers' responses in the first year following the fuel efficiency improvement. In contrast, long-run estimates take into account the time required by consumers to change their capital stock, i.e. to change vehicles. For that reason, policies aiming to increase fuel efficiency of new cars would be better informed by estimates of long-run rebound effects than by estimates of short-run ones. Table 3 presents summary statistics for short- and long-run estimates of the rebound effect. For the purposes of this meta-analysis, estimates from static econometric specifications and estimates defined as medium-rum (Gillingham, 2014) are grouped together with long-run estimates (see also Sorrell, Dimitropoulos and Sommerville, 2009).

Table 3 reveals a significant divergence between short- and long-run estimates. Short-run rebound effects are estimated to be in the area of 12%, whereas log-run effects are, on average, about 32% (see column labelled "Weighted B"). Short-run rebound effects are smaller than long-run ones regardless of the elasticity measure used to estimate them and the weighting approach used to analyse them. Short-run estimates of the most direct measure of the rebound effect, i.e. the elasticity with respect to fuel efficiency, are unfortunately extremely few to justify the extraction of a reliable conclusion. Long-run estimates of this elasticity point to a much smaller effect with an average magnitude of 6.4% (weighting scheme B). Nevertheless, this may be attributed to the strong influence of studies on Danish micro-data.

Table 3. Summary statistics of the rebound effect by time horizon and elasticity measure

	No. of Estimates	Unweighted mean	Weighted A	Weighted B	Min	Max
All estimates						
Short-run	324	0.094	0.139	0.122	-0.372	0.684
Long-run	814	0.293	0.341	0.317	-0.643	1.686
Elasticity w.r.t fuel efficiency						
Short-run	21	-0.133	-0.021	0.009	-0.372	0.684
Long-run	186	0.311	0.257	0.064	-0.643	1.329
Elasticity w.r.t fuel costs						
Short-run	183	0.102	0.139	0.092	-0.280	0.574
Long-run	248	0.267	0.393	0.310	0.007	1.453
Elasticity w.r.t fuel price						
Short-run	120	0.122	0.135	0.128	-0.108	0.587
Long-run	380	0.301	0.330	0.361	-0.409	1.686

Note: Estimates from static econometric specifications and estimates defined in the primary study as "medium-run" are considered here as long-run elasticities.

5. META-REGRESSION ANALYSIS

Obtaining robust estimates of the rebound effect is only one goal of this meta-analysis. A second aim is to identify sources of heterogeneity and potential biases. In Table 2 above, large standard deviations indicate a high degree of heterogeneity in estimates. Several sources of heterogeneity among primary studies have been identified in previous studies (see e.g. Gillingham, Rapson and Wagner, 2015; Greening, Greene and Difiglio, 2000; Sorrell and Dimitropoulos, 2008). The geographical and time coverage of the study are among the first, rather obvious, suspect causes of heterogeneity. Heterogeneity can also exist, however, due to differences in the type of data used (e.g. cross-sectional, panel, or time series; disaggregate or aggregated). Differences may also stem from the quality of data; some datasets are more prone to measurement error than others.[12] Other methodological differences may be present, including differences in the econometric technique deployed, the control variables included in primary studies' empirical models, or the treatment of endogenously determined variables.

The meta-regression analysis is based on the following econometric model:

$$R_i = \alpha + \beta_1 S_i + \boldsymbol{\beta_2}\mathbf{M_i} + \boldsymbol{\beta}_3\mathbf{X_i} + \boldsymbol{\beta}_4\mathbf{C_i} + \varepsilon_i \quad (1)$$

[12] Weber and Farsi (2014) compare data for Switzerland. In one of their models, they use data on self-reported travel for a reference day to project annual VKT, while in another they use very accurate GIS travel data. They find a very weak correlation of 0.2 between the two measures of distance travelled, indicating there may be significant differences between self-reported travel data and rigorously measured travel data.

where R denotes the rebound effect estimate from the primary study, S is an indicator taking the value of unity when the elasticity concerns the short run, and the value of zero when it concerns the long or medium run, and **M** is a vector of dummy variables indicating the elasticity measure estimated in the primary study. The aim is to investigate whether long-run estimates are indeed significantly larger than short-run ones and whether the elasticity measure used to estimate the rebound effect has an impact on its estimated magnitude. The vector of dummy variables **X** contains elements related to different study characteristics (e.g. type of data and econometric technique used), and vector **C** denotes specific macro-level variables which may be influencing the rebound effect in the country and time period analysed in the primary study, such as income and gasoline prices. Parameter α and (vectors of) parameters $\beta_{(.)}$ are to estimated, and ε is an error term.

Table 4 presents the definition of the explanatory variables used in the meta-regression analysis, while Table 5 presents the results of five meta-regression models. In addition to a simple ordinary least squares (OLS) specification, Table 5 shows the results of two models estimated by weighted least squares (WLS). The two WLS models correspond to the two weighting schemes presented in the previous section. The results presented in the column titled “WLS A” are based on weights equal to the inverse of the number of estimates derived per group of studies. For “WLS B”, each estimate is weighted by the product of the weight used in “WLS A” and the sample size used to derive this estimate (see also Van Houtven, Powers and Pattanyak, 2007).[13]

The last two columns of Table 5 present results from the estimation of fixed and random effects panel data models. These models assume that each group of primary studies provides a panel of rebound effect estimates. Panel data methods can more effectively take into account the potential correlation of estimates coming from the same study (see also Nelson and Kennedy, 2009). The panel data equivalent of Equation (1) is as follows:

$$R_{jk} = \gamma_j + \delta_1 S_{jk} + \boldsymbol{\delta}_2 \mathbf{M}_{\mathbf{jk}} + \boldsymbol{\delta}_3 \mathbf{X}_{\mathbf{jk}} + \boldsymbol{\delta}_4 \mathbf{C}_{\mathbf{jk}} + u_{jk} \tag{2}$$

where R_{jk} denotes the kth rebound effect estimate from group of studies j. The group-specific parameter γ and (vectors of) parameters $\delta_{(.)}$ are to be estimated. The error term of the model is denoted by u.

[13] The sample size used for the estimation of different models often varies within primary studies.

Table 4. Description and summary statistics for the variables used in the meta-regression analysis

Explanatory variable	Description	Observations	Mean	Std. deviation	Min	Max
Short-run estimate	= 1, if estimate refers to the short run; = 0, otherwise.	1138	0.285	-	0	1
Elasticity w.r.t. fuel costs	= 1, if estimate of elasticity w.r.t. fuel costs in primary study; = 0, otherwise.	1138	0.379	-	0	1
Elasticity w.r.t. fuel price	= 1, if estimate of elasticity w.r.t. fuel price in primary study; = 0, otherwise.	1138	0.439	-	0	1
Percentage of years in oil crisis	Percentage of years in the period 1974-1981 in the total time period considered in the study.	1138	15.063	28.723	0	100
Micro-data	= 1, if primary study uses micro-level (e.g. survey) data; = 0, otherwise.	1138	0.605	-	0	1
Self-reported data on distance travelled	= 1, if data on distance travelled are only self-reported; = 0, otherwise.	1138	0.257	-	0	1
Single car	= 1, if elasticity estimate is specific to households with one car; = 0, otherwise.	1138	0.105	-	0	1
Country-specific	= 1, if estimates are based on an analysis for a single country; = 0, if estimates are based on a cross-country analysis.	1138	0.984	-	0	1
GDP per capita	Average of GDP per capita (2010 USD PPP) in the time period covered by the data	1120	36978.5	8846.6	4362.9	51155.8
Gasoline price	Average real gasoline price per litre (2010 USD PPP) in the time period covered by the data	1119	0.881	0.398	0.420	3.600

Note: Data on GDP per capita are extracted from the OECD National Accounts database (OECD, 2016a) and the World Bank's database on World Development Indicators (data for India, World Bank, 2016). Data on real gasoline prices are calculated from IEA's database on Energy Prices and Taxes (IEA, 2016a, 2016b, 2016c; OECD, 2016b). Databases were last accessed in January 2016.

The presented specifications are the outcome of extensive exploratory analysis, where the performance of several other explanatory variables was tested. For example, it was investigated whether rebound effect estimates varied with data type (e.g. cross-sectional data vs. time-series) or econometric method used (instrumental variable methods vs. methods not taking the endogeneity of fuel efficiency into account). The econometric performance of other macro-econometric variables, such as population density and density of public transport infrastructure, was also tested. However, these variables were dropped from final specifications due to multicollinearity concerns and for the sake of parsimony.

A first important assumption that was interesting to test was whether long-run estimates are systematically different from short-run ones. Estimates explicitly designated as "short-run" or "long-run" in the primary study are labelled as such. These estimates usually come from dynamic specifications; that is, the primary regressions include at least one lagged value of the dependent variable in the set of explanatory variables. Intuitively, the short run is generally understood as the time horizon during which capital stock cannot be changed. This implies that the long run can be considered as enough time to allow consumers to change vehicles.

However, many estimates are not explicitly defined as long- or short-run elasticities. This is often the case when an estimate is derived from a static specification. This is a common issue encountered in most literature reviews and meta-analyses (see e.g. Espey, 1998; Hanly, Dargay and Goodwin, 2002; Goodwin, Dargay and Hanly, 2004; Graham and Glaister, 2004). Authors take various approaches to this issue. In this meta-analysis, estimates from static specifications tend to be closer to long-run estimates. This seems intuitive, as static estimation does not remove or consider the past values of a variable, as done when obtaining short-run estimates. As a result, estimates from static specifications are considered here as long-run elasticities. Some elasticities which were defined in the primary study as "medium-run" – being closer to two years – are also reclassified as long-run for the purpose of this meta-analysis. Since it seems likely that individuals can change vehicles within this two-year timeframe, reclassifying the estimates as long-run should maintain the validity of the time horizon distinctions.

Table 5. Meta-regression results

	OLS		WLS A		WLS B		Random Effects		Fixed Effects [a]	
Variables	estimate	std. error	estimate	std. error	estimate	std. error	estimate	std. error	estimate	std. error
Short-run estimate	-0.176***	(0.029)	-0.182***	(0.035)	-0.172***	(0.029)	-0.170***	(0.028)	-0.172***	(0.030)
Elasticity w.r.t fuel costs	0.091*	(0.050)	0.188**	(0.071)	0.206**	(0.087)	0.112**	(0.056)	0.109*	(0.059)
Elasticity w.r.t fuel price	0.099*	(0.050)	0.131**	(0.057)	0.250***	(0.083)	0.123*	(0.073)	0.125	(0.077)
Percentage of years in oil crisis	-0.002***	(0.000)	-0.002**	(0.001)	-0.000	(0.002)	-0.002***	(0.001)	-0.001**	(0.001)
Micro-data	0.152***	(0.040)	0.152**	(0.062)	0.174***	(0.045)	0.149***	(0.047)		
Self-reported data on distance travelled	0.071**	(0.035)	-0.011	(0.064)	0.141***	(0.052)	0.003	(0.034)	-0.006	(0.044)
Single car	0.119***	(0.041)	0.028	(0.071)	0.145***	(0.038)	0.099***	(0.037)	0.101**	(0.039)
Country-specific	-0.137***	(0.027)	-0.088***	(0.030)	-0.174***	(0.060)	-0.036	(0.030)	-0.007	(0.035)
Country-specific x log(GDP per capita)	-0.215***	(0.079)	-0.055	(0.091)	-0.229	(0.143)	-0.279***	(0.058)	-0.333***	(0.034)
Country-specific x log(Gasoline price)	0.006	(0.057)	0.162*	(0.084)	0.031	(0.054)	0.068	(0.061)	0.076	(0.076)
Constant	0.287***	(0.039)	0.217***	(0.056)	0.163	(0.104)	0.215***	(0.057)	0.261***	(0.056)
Observations		1137		1137		1137		1137		1137
R-squared		0.304		0.298		0.478		0.269		0.490
Adjusted R-squared		0.298		0.291		0.473				0.457

Note: Robust standard errors, clustered by group of primary studies (60 groups), in parentheses. ***,** and * indicate that the parameter is statistically significant at the 1%, 5% and 10% level respectively. WLS A is based on weights equal to the inverse of the number of estimates per group of stud. WLS B is based on weights equal to the product of the weights used in WLS A and the sample size used for the estimation of the effect in the primary study.

[a] The Sargan-Hansen test for overidentifying restrictions suggests that the fixed-effects specification should be preferred to the random-effects one (p-value=0.000).

The constants of the models can be interpreted as the average rebound effect when all explanatory variables take the value of zero and GDP per capita and gasoline prices are at the means of the sample. Taking the constant of the OLS model as an example, the long-run rebound effect is about 29% when estimated by the elasticity with respect to fuel efficiency and on the basis of cross-country aggregate data from odometer readings (or a mix of odometer readings and self-reported data).

Short-run estimates of the rebound effect are consistently higher than long-run ones across specifications. Estimation results of “WLS B”, the authors’ preferred specification, reveal that long-run estimates of the rebound effect are at least 17 percentage points lower than short-run ones. This finding confirms that the time horizon of the estimate is one of the most important determinants of heterogeneity in primary estimates. This is both highly intuitive and consistent with the existing literature (see, for example, Goodwin, Dargay and Hanly, 2004; Graham and Glaister, 2004; Small and Van Dender, 2007). Hanly, Dargay and Goodwin (2002) outline three main ways individuals can adapt to increases in the cost of driving: (i) change driving styles (e.g. less heavy acceleration and braking); (ii) shift the pattern of journeys such that more of them occur in fuel-efficient contexts (e.g. light traffic at moderate speeds, as compared with very low or very high speeds); and (iii) change to more fuel-efficient vehicles (e.g. newer, better maintained, smaller or more technically advanced). While (i) and (ii) can be enacted in the short run, changing vehicles can only be enacted in the long run. As individuals have the flexibility to choose the fuel efficiency of their vehicle, one would indeed expect greater increases in travel demand in the long run.

Section 2 discussed the various definitions of the rebound effect and the assumptions underlying their use. It is, however, important to test whether the magnitude of empirical estimates of the rebound effect is affected by the elasticity measure used in the primary study. Meta-regression results reveal that the elasticity of travel demand with respect to fuel costs (definition 2) and fuel price (definition 3) result in higher estimates of the rebound effect than the elasticity with respect to fuel efficiency (definition 1 – reference category in the econometric models). Even though the magnitude of the difference varies considerably among models, the difference between estimates based on definition 1 and estimates based on definitions 2 and 3 is especially large in WLS B, amounting to about 21 (elasticity with respect to fuel costs) to 25 (elasticity with respect to fuel price) percentage points.[14] This finding raises concerns regarding the validity of the assumptions underlying the theoretical equivalence of the three definitions and implies that estimates of the rebound effect based on the elasticity with respect to fuel costs or fuel price may be misleadingly high. The use of the most direct measure of the rebound effect, the elasticity of travel demand with respect to fuel efficiency, leads to significantly more conservative estimates of the rebound effect in and should be preferred to other measures whenever this is possible.

Relevant elasticities, and therefore rebound effects, may have been lower during the oil crises of the 1970s, as fuel supply was constrained. The models use the percentage of years in the period of the oil crises (1974-1981) in the total number of years considered in the primary study to test this assumption (cf. Brons et al., 2008; Espey, 1998). The assumption is statistically confirmed in almost all models (with the exception of WLS B), which point to a *circa* 2 percentage-point reduction of the rebound effect for every 10-point increase in the percentage of years in the oil crisis.

The use of micro-data, instead of aggregate ones, results in significantly higher estimates of the rebound effect. Estimates based on micro-data can be as high as 17 percentage points larger. This can be attributed to an assumption commonly made in empirical studies using microdata. This assumption is that vehicle fuel economy is uncorrelated to other vehicle and household characteristics (Linn, 2016). For example, econometric models in primary studies may fail to control for vehicle attributes like comfort and engine power which are correlated with fuel efficiency. These studies are likely to overestimate the rebound effect, as they will attribute the effect of e.g. increased comfort on VMT to improved fuel efficiency.

Estimates based on self-reported data have been suggested to be larger in absolute terms, compared with estimates based on odometer readings. The preferred specification (WLS B) provides evidence in support of this argument, showing that rebound effect estimates based solely on self-reported data can be as high as 14 percentage points higher than estimates based on odometer readings or a mix of data sources. However, most of the other specifications do not provide similar evidence, revealing that the result is not robust to alternative modelling assumptions.

Rebound effect estimates for single-car households are about 15 percentage points higher than estimates for multi-vehicle ones and estimates for all households together (WLS B). The existence of a single car in the household implies that all additional travel in response to a fuel efficiency improvement will occur in this car. On the other hand, multivehicle households may substitute the use of the less fuel-efficient car with the use of the more fuel-efficient one. When the analysis is made at the vehicle level (and not at the household level), rebound effect estimates will depend on the car being analysed. This potentially confounding factor is not present in the analysis of single-car households and rebound effect estimates can be more accurately estimated.

Rebound effect estimates vary by country, but it is probably more interesting to investigate particular country characteristics which may be responsible for this variation. Rebound effect estimates are matched

[14] Differences between elasticities based on definitions 2 and 3 are not statistically significant.

with macroeconomic and transport infrastructure characteristics to this end.[15] Estimates are matched with real gasoline prices, GDP per capita (in constant prices and PPPs), railway density, population density, the percentage of urban population living in urban areas, and other variables which may theoretically affect the magnitude of the rebound effect. Out of these variables, only GDP per capita and real gasoline prices appeared to both significantly influence rebound effect estimates and not raise multicollinearity concerns and are, thus, included in the presented specifications.

Earlier studies of the rebound effect suggest that it decreases with income (e.g. Small and van Dender, 2007). Meta-regression results from most models (except for the WLS ones) provide support to this earlier finding; for example, the fixed effects model points to a reduction of about 0.33 percentage points for each 1% increase in real GDP per capita (constant prices and PPPs). Concurring with theoretical arguments provided in the literature, the authors of this meta-analysis are inclined to attribute this finding to the inevitable trade-off between fuel costs and time costs involved in driving more. The opportunity cost of time increases with income and, thus, richer households are likely to take advantage of improved fuel efficiency to a lesser extent than less well-off households (see also Small and Van Dender, 2007; Sorrell and Dimitropoulos, 2008; Sorrell, Dimitropoulos and Sommerville, 2009).

Higher gasoline prices may imply higher rebound effect estimates for at least two reasons. First, higher gasoline prices are, *ceteris paribus*, associated with less intensive car use. Thus, even if individuals respond to improved fuel efficiency by increasing travelled distances by the same level (e.g. 1000 km per year), the increase will be higher in *percentage* terms in the country were gasoline prices are higher. Second, individuals may be tempted to increase private car travel to a larger extent (in absolute terms) in countries with high gasoline prices. Before the fuel efficiency improvement, it was cheaper to make some trips by public transport than by car. This is much more likely in countries where gasoline prices are high. After the fuel efficiency improvement, private car travel becomes more competitive and households are more likely to substitute private car for public transport for those trips. However, meta-regression results do not provide convincing evidence that higher gasoline prices are associated with larger rebound effects (cf. Sims et al., 2014). The effect is statistically significant only in WLS A.

[15] For each estimate of a primary study, the matching approach considers the time coverage of the data used to produce that estimate. The average of each macro-level variable of interest for that time period and country is then calculated (ignoring possible gaps in time series). The resulting averages of macroeconomic and other country characteristics are finally matched back to the rebound effect estimates produced by primary studies.

6. CONCLUSIONS AND POLICY IMPLICATIONS

This report presents a meta-analysis of 76 primary studies and 1138 estimates of the direct rebound effect in road transport. The aim is to provide a useful synthesis of past work and inform ongoing discussions about its magnitude. Empirical results reveal that the magnitude of the rebound effect in road transport can be considered to be, on average, in the area of 20%. However, estimates vary significantly with the time horizon considered. Estimates for the long run are significantly larger than estimates for the short run. The short-run rebound effect is estimated to be in the area of 12%, whereas the long-run effect about 32%.

Estimates vary significantly with the elasticity used to measure the rebound effect. The most direct measure of it, i.e. the elasticity of travel with respect to fuel efficiency, results in much more conservative estimates than rebound effect measures exploiting variation in fuel prices. In the case of fuel efficiency standards in particular, the long-run estimate is, in theory, the most relevant, as the fuel efficiency of a vehicle cannot be significantly changed in the short run. The meta-analysis further reveals significant differences in the estimates of the rebound effect across countries. Cross-country differences can be to some extent attributed to differences in per capita income. In particular, lower GDP per capita is associated with larger rebound effects. Therefore, caution should be exercised when assuming a certain magnitude of the rebound effect, as it may vary significantly across regions.

The existence of a rebound effect impacts policy significantly. Indeed, results suggest that a 10% increase in fuel efficiency would result in a *circa* 3% increase in travel demand in the long run. This induced travel partially offsets the expected energy savings from an increase in fuel efficiency, in addition to contributing to mileage-related externalities like higher levels of non-exhaust air pollution, noise, congestion and traffic accidents. Induced travel implies that even in the presence of stringent fuel efficiency standards, the implementation of price instruments is key to ensure that road transport externalities are effectively addressed. Rapid and significant improvements in fuel efficiency, along with a gradual shift towards electric transport, will also soon pose important fiscal challenges to policy makers, who will perhaps have to consider alternatives to fuel taxation. In light of these environmental and fiscal challenges, it is probably timely to reconsider the implementation of distance-based taxes, which can provide for an efficient means of addressing the externalities of car travel and ensuring the stability of an important source of fiscal revenue. As these external costs (e.g. congestion) vary across space and over time, distance-based taxes will be more efficient if they are space- and time-variant (see also Johansson and Schipper, 1997).

In addition to identifying the factors responsible for the variation in rebound effect estimates, the meta-regression model developed in this paper can serve as a tool to assist policy analysis in contexts where rebound effect estimates are missing. This can be especially useful in countries where it is difficult to collect data on travel demand and resources for relevant analyses are scarce. Importing data on macro-level variables which are more readily available (GDP per capita and gasoline prices), the analyst can derive estimates of potential rebound effects in such contexts. However, these estimates should be treated with caution, especially in countries with very different macroeconomic characteristics, transport infrastructure and rates of new technology adoption than the ones analysed here.

At the same time, it may prove useful to collect and use national data to estimate the rebound effect in other countries. Estimates from developing countries, in particular, seem to be lacking in the existing literature. Due to numerous differences in household income, road and public transport infrastructure, travel behaviour, car ownership and technology adoption between developed and developing nations, there seems little reason to assume a consistent magnitude of the rebound effect across regions. Provided that car travel demand is expected to increase considerably in emerging economies in the following years – with potentially serious environmental consequences – it is useful to collect more empirical evidence of the impact of improved fuel efficiency on car ownership and use in those contexts. This could be a promising avenue for future research.

REFERENCES

Ajanovic, A. and R. Haas (2012), "The role of efficiency improvements vs. price effects for modeling passenger car transport demand and energy demand – Lessons from European countries", *Energy Policy*, Vol. 41/ 0, pp. 36-46.

Ajanovic, A., L Schipper and R. Haas (2012), "The impact of more efficient but larger new passenger cars on energy consumption in EU-15 countries", *Energy,* Vol. 48/1, pp. 346-355.

Baltagi, B.H. (2005), *Econometric Analysis of Panel Data*, 3rd edition, John Wiley and Sons, Ltd., West Sussex, England.

Barla, P. et al. (2009), "Traveled Distance, Stock and Fuel Efficiency of Private Vehicles in Canada: Price Elasticities and Rebound Effect", *Transportation*, Vol. 36/4, pp, 389-402.

Bento, A.M. et al. (2009), "Distributional and Efficiency Impacts of Increased US Gasoline Taxes", *The American Economic Review*, Vol. 99/3, pp. 667-699.

Bergel, R., A. Depire, and A. Mutter (2002), "Modélisation des trafics de voyageurs et de marchandises", Rapport de convention SES/INRETS no.00-5815, Rapport DERA no. 2001-03.

Brons, M. et al. (2008), "A meta-analysis of the price elasticity of gasoline demand", A SUR approach. *Energy Economics*, Vol 30/5, pp. 2105-2122.

Cervero, R. and M. Hansen (2002), "Induced Travel Demand and Induced Road Investment: A Simultaneous Equation Analysis", *Journal of Transport Economics and Policy*, Vol. 36/3, pp. 469-490.

Chugh, R. and M. Cropper (2014), "The Welfare Effects of Fuel Conservation Policies in the Indian Car Market". *NBER Working Paper* No. w20460, National Bureau of Economic Research.

Concas, S. (2012), "Highway Capital Expenditures and Induced Vehicle Travel", *Center for Urban Transportation Resea*rch, University of South Florida.

D' Haultfœuille, X., P. Givord and X. Boutin (2014), "The Environmental Effect of Green Taxation: The Case of the French Bonus/Malus", *Economic Journal*, Vol. 124/578, F444–F480.

Daniels, M. and A.B. Hill (1952), "Chemotherapy of pulmonary tuberculosis in young adults: An analysis of the combined results of three medical research council trials", *British Medical Journal*, Vol. 1/4769, pp. 1162-1168.

Dargay, J. (2007). "The effect of prices and income on car travel in the UK*", Transportation Research Part A: Policy and Practice*, Vol. 41/10, pp. 949–960.

De Borger, B., I. Mulalic and J. Rouwendal (2016), "Measuring the rebound effect with micro data: A first difference approach", *Journal of Environmental Economics and Management*, Vol. 79, pp. 1–17.

de Jong, G. (1996), "A disaggregate model system of vehicle holding duration, type choice and use", *Transportation Research Part B: Methodological*, Vol. 30/4, pp. 263-276.

de Jong, G. and H. Gunn (2001), "Recent Evidence on Car Cost and Time Elasticities of Travel Demand in Europe", *Journal of Transport Economics and Policy*, Vol. 35/2, pp. 137-160.

de Jong, G. et al. (2009), "The impact of fixed and variable costs on household car ownership", *Journal of Choice Modelling, Vol. 2*/2, pp. 173-199.

Dillon, H. S., J-D. Saphores and M.G. Boarnet (2015), “The impact of urban form and gasoline prices on vehicle usage: Evidence from the 2009 National Household Travel Survey”, *Research in Transportation Economics*, Vol. 52, pp. 23-33.

Espey, M. (1998), "Gasoline demand revisited: an international meta-analysis of elasticities. *Energy Economics"*, Vol. 20/3, pp. 273-295.

Feng, Y., D. Fullerton and L. Gan (2013), “Vehicle choices, miles driven, and pollution policies”, *Journal of Regulatory Economics*, Vol. 44/1, pp. 4–29.

Ficano, C. C. and P. Thompson (2014), "Estimating Rebound Effects in Personal Automotive Transport: Gas Price and the Presence of Hybrids", *American Economist*, Vol. 59/2, pp. 167-175.

Fridstrøm, L. (1998), "Car ownership, road use, accidents, and injuries", TØI Report 402, Oslo.

Frondel, M., F. Martinez Flores and C. Vance (2016), “Heterogeneous Rebound Effects: Comparing Estimates from Discrete-Continuous Models”, *Ruhr Economic Papers* 601, Rheinisch-Westfälisches Institut für Wirtschaftsforschung, Ruhr-Universität Bochum, Universität Dortmund, Universität Duisburg-Essen.

Frondel, M., J. Peters and C. Vance (2008), "Identifying the Rebound: Evidence from a German Household Panel", *The Energy Journal*, pp. 145-163.

Frondel, M., J. Peters and C. Vance (2007), “Identifying the Rebound: Evidence from a German Household Panel”, *Ruhr Economic Papers* 32, Rheinisch-Westfälisches Institut für Wirtschaftsforschung, Ruhr-Universität Bochum, Universität Dortmund, Universität Duisburg-Essen.

Frondel, M., N. Ritter and C. Vance (2012), "Heterogeneity in the rebound effect: Further evidence for Germany", *Energy Economics*, Vol. 34/2, pp. 461-467.

Frondel, M. and C. Vance (2013), "Fuel Taxes versus Efficiency Standards – An Instrumental Variable Approach", *Ruhr Economic Papers* 445, Rheinisch-WestfälischesInstitut für Wirtschaftsforschung, Ruhr-Universität Bochum, Universität Dortmund, Universität Duisburg-Essen.

Frondel, M. and C. Vance (2011), "Re-identifying the Rebound: What About Asymmetry?", *Ruhr Economic Papers* 276, Rheinisch-Westfälisches Institut für Wirtschaftsforschung, Ruhr-Universität Bochum, Universität Dortmund, Universität Duisburg-Essen.

Frondel, M. and C. Vance (2009), “Do High Oil Prices Matter? Evidence on the Mobility Behavior of German Households”, *Environmental and Resource Economics*, Vol. 43/1, pp. 81–94.

Gately, D. (1990), "The U.S. Demand for Highway Travel and Motor Fuel", *The Energy Journal*, Vol. 11/3, pp. 59-73.

Gillingham, K. (2014), "Identifying the elasticity of driving: Evidence from a gasoline price shock in California", *Regional Science and Urban Economics*, Vol. 47, pp. 13-24.

Gillingham, K., A. Jenn and I. Azevedo (2015), "Heterogeneity in the response to gasoline prices: Evidence from Pennsylvania and implications for the rebound effect", *Energy Economics*, Vol. 52, pp. S41–S52.

Gillingham, K. and A. Munk-Nielsen (2015), "The Tail Wagging the Dog: Commuting and the Fuel Price Response in Driving", *Working Paper*, Department of Economics, University of Copenhagen.

Gillingham, K. and K. Palmer (2014), "Bridging the Energy Efficiency Gap: Policy Insights from Economic Theory and Empirical Evidence", *Review of Environmental Economics and Policy*, Vol. 8/1, pp. 18-38.

Gillingham, K., D. Rapson and G. Wagner (2014), "The Rebound Effect and Energy Efficiency Policy", *Review of Environmental Economics and Policy*, Vol. 10/1, pp. 68-88.

Gillingham, K., et al. (2015), “A Dynamic Model of Vehicle Ownership, Type Choice, and Usage”, *Working Paper*, Department of Economics, University of Copenhagen.

Glass, G.V. (1976), "Primary, Secondary, and Meta-Analysis of Research", *Educational Researcher*, Vol. 5/10, pp. 3-8.

Goldberg, P.K. (1998), "The Effects of the Corporate Average Fuel Efficiency Standards in the US", *The Journal of Industrial Economics*, Vol. 46/1, pp. 1-33.

Goldberg, P.K. (1996), "The Effects of the Corporate Average Fuel Efficiency Standards in the US", *NBER Working Paper Series*, No 5673, National Bureau of Economics Research, Cambridge, MA.

Gonzalez, R.E. and G.A. Marrero (2012), "Induced road traffic in Spanish regions: A dynamic panel data model", *Transportation Research Part A*, Vol. 46, pp. 435-445.

Goodwin, P., J. Dargay and M. Hanly (2004), "Elasticities of Road Traffic and Fuel Consumption with Respect to Price and Income: A Review", *Transport Reviews*, Vol. 24(3), pp. 275-292.

Graham, D.J. and S. Glaister (2004), "Road Traffic Demand Elasticity Estimates: A Review", *Transport Reviews*, Vol 24/2, pp. 261-274.

Graham, D.J. and S. Glaister (2002), "The Demand for Automobile Fuel: A Survey of Elasticities", *Journal of Transport Economics and Policy*, Vol. 36/1, pp. 1-25.

Greene, D.L. (2012), "Rebound 2007: Analysis of U.S. light-duty vehicle travel statistics", *Energy Policy*, Vol. 41/0, pp. 14-28.

Greene, D.L. (1992), "Vehicle Use and Fuel Economy: How Big is the "Rebound" Effect?", *The Energy Journal*, Vol. 13/1, pp. 117-143.

Greene, D.L. and P.S. Hu (1984), "The Influence of the Price of Gasoline on Vehicle Use in Multivehicle Households", *Transportation Research Record,* Vol. 988, pp. 19-24.

Greene, D.L., J.R. Kahn and R.C. Gibson (1999), "Fuel Economy Rebound Effect for U.S. Household Vehicles", *The Energy Journal*, Vol. 20/3, pp. 1-31.

Greening, L.A., D.L. Greene and C. Difiglio (2000), "Energy efficiency and consumption — the rebound effect — a survey", *Energy Policy*, Vol. 28/6-7, pp. 389-401.

Greening, L.A. et al. (1995), "Use of region, life-cycle and role variables in the short-run estimation of the demand for gasoline and miles travelled", *Applied Economics*, Vol. 27/7, pp. 643-656.

Hanly, M., J.M. Dargay and P.B Goodwin (2002), *Review of income and price elasticities in the demand for road traffic*, University College London, London.

Hansen, M., and Y. Huang (1997), "Road supply and traffic in California urban areas", *Transportation Research Part A: Policy and Practice*, Vol. 31/3, pp. 205-218.

Harding, M. (2014), "The Diesel Differential: Differences in the Tax Treatment of Gasoline and Diesel for Road Use", *OECD Taxation Working Papers*, No. 21, OECD Publishing, Paris, *http://dx.doi.org/10.1787/5jz14cd7hk6b-en*.

Haughton, J. and S. Sarkar (1996), "Gasoline Tax as a Corrective Tax: Estimates for the United States, 1970-1991", *The Energy Journal*, Vol. 17/2, pp. 103-126.

Hensher, D.A., F.W. Milthorpe and N.C. Smith (1990), "The Demand for Vehicle Use in the Urban Household Sector", *Journal of Transport Economics and Policy*, Vol. 24/May, pp. 119-137.

Hensher, D.A. and N.C. Smith (1986), "A structural model of the use of automobiles by households: a case study of urban Australia", *Transport Reviews*, Vol. 6/1, pp. 87-111.

Hymel, K.M., K.A. Small, K.A. and K. van Dender (2010), "Induced demand and rebound effects in road transport", *Transportation Research Part B: Methodological*, Vol. 44/10, pp. 1220-1241.

Hymel, K.M. and K.A. Small (2015), "The rebound effect for automobile travel: Asymmetric response to price changes and novel features of the 2000s", *Energy Economics*, Vol. 49/May, pp. 93-103.

IEA (2016a), "End-use prices: Indices of energy prices by sector", *IEA Energy Prices and Taxes Statistics* (database), *http://dx.doi.org/10.1787/data-00444-en*.

IEA (2016b), "End-use prices: Energy prices in national currency per unit", *IEA Energy Prices and Taxes Statistics* (database), *http://dx.doi.org/10.1787/data-00441-en*.

IEA (2016c), "End-use prices: Energy prices for selected non-OECD Countries", *IEA Energy Prices and Taxes Statistics* (database), *http://dx.doi.org/10.1787/data-00683-en*.

Jevons, W.S. (1865), *The Coal Question: An Inquiry Concerning the Progress of the Nation, and the Probable Exhaustion of Our Coal-Mines*, Macmillan and Co., London.

Johansson, O. and L. Schipper (1997), "Measuring the Long-Run Fuel Demand of Cars: Separate Estimations of Vehicle Stock, Mean Fuel Intensity, and Mean Annual Driving Distance", *Journal of Transport Economics and Policy*, Vol. 31/3, pp. 277-292.

Jones, C.T. (1993), "Another Look at U.S. Passenger Vehicle Use and the 'Rebound' Effect from Improved Fuel Efficiency", *Energy Journal*, Vol. 14/4, pp. 99-110.

Kemel, E., R. Collet, R. and L. Hivert (2011), "Evidence for an Endogenous Rebound Effect Impacting Long-Run Car Use Elasticity to Fuel Price", *Economics Bulletin*, Vol. 31/4, pp. 2777-2786.

Khazzoom, J.D. (1980), "Economic Implications of Mandated Efficiency in Standards for Household Appliances", *The Energy Journal*, Vol. 1/4, pp. 21-40.

Knittel, C.R. and R. Sandler (2011), "Carbon Prices and Automobile Greenhouse Gas Emissions: The Extensive and Intensive Margins", in D. Fullerton and C. Wolfram (eds.), *The Design and Implementation of U.S. Climate Policy*, University of Chicago Press, Chicago, pp. 287-299.

Knittel, C.R. and R. Sandler (2010), "Carbon prices and automobile greenhouse gas emissions: the extensive and intensive margins", *NBER Working Papers*, No. 16482, National Bureau of Economic Research, Cambridge, MA.

Lamonde, B. (2007). "Estimation d'un modèle agrégé du nombre de kilomètres parcourus, du taux de consommation moyen de carburant et du nombre de véhicules légers au Canada", Mémoire de maître des arts (M.A.), Département d'Économique, Faculté des Sciences Sociales, Université Laval, Québec.

Lee, S. (2015). *The role of urban spatial structure in reducing VMT and GHG emissions*. Ph.D. thesis, University of Illinois at Urbana-Champaign.

Leung, W. (2015), "Switching and Sharing: Gasoline Prices and Household Fleet Utilization", Working Paper, University of California, San Diego Department of Economics.

Li, S., J. Linn and E. Muehlegger (2014), "Gasoline Taxes and Consumer Behavior", *American Economic Journal: Economic Policy*, Vol. 6(4), pp. 302-342.

Linn, J. (2016), "The Rebound Effect for Passenger Vehicles", *The Energy Journal*, Vol. 37/2, pp. 257–288.

Liu, Y. (2011), *Essays on Fuel Efficiency and Vehicle Demand Dynamics*, Ph.D. dissertation, University of Texas at Austin.

Mannering, F. L. (1986), "A note on endogenous variables in household vehicle utilization equations", *Transportation Research Part B: Methodological*, Vol. 20/1, pp. 1-6.

Mannering, F.L. (1983), "An econometric analysis of vehicle use in multivehicle households", *Transportation Research Part A: General*, Vol. 17/3, pp. 183-189.

Mannering, F. and C. Winston (1985), "A Dynamic Empirical Analysis of Household Vehicle Ownership and Utilization", *The RAND Journal of Economics*, Vol. 16/2, pp. 215–236.

Matiaske, W., R. Menges and M. Spiess (2012), "Modifying the rebound: It depends! Explaining mobility behavior on the basis of the German socio-economic panel", *Energy Policy*, Vol. 41/0, pp. 29-35.

Mayo, J.W. and J.E. Mathis (1988), "The effectiveness of mandatory fuel efficiency standards in reducing the demand for gasoline", *Applied Economics*, Vol. 20/2, pp. 211-219.

Mizobuchi, K. (2008), "Rebound Effect of Passenger Vehicles in Japan: Does High Environmental Awareness Decrease the Rebound Size?", *Paper presented at the EAERE 16th Annual Conference*, Gothenburg, 25-28 June..

Munk-Nielsen, A. (2015), "Diesel Cars and Environmental Policy", *Working Paper*, Department of Economics, University of Copenhagen.

Noland, R.B. (2001), “Relationships between highway capacity and induced vehicle travel”, *Transportation Research Part A: Policy and Practice*, Vol. 35/1, pp. 47-72.

Noland, R. and W. Cowart (2000), "Analysis of Metropolitan Highway Capacity and the growth in vehicle miles of travel", *Transportation*, Vol. 27/4, pp. 363-390.

O’Rourke, K. (2007), "A historical perspective on meta-analysis: dealing quantitatively with varying study results", *Journal of the Royal Society of Medicine*, Vol. 100/12, pp. 579-582.

Odeck, J. and K. Johansen (2016), "Elasticities of fuel and traffic demand and the direct rebound effects: An econometric estimation in the case of Norway", *Transportation Research Part A: Policy and Practice*, Vol. 83, pp. 1–13.

OECD (2016a), "Aggregate National Accounts, SNA 2008 (or SNA 1993): Gross domestic product", *OECD National Accounts Statistics* (database). *http://dx.doi.org/10.1787/data-00001-en*.

OECD (2016b), "PPPs and exchange rates", *OECD National Accounts Statistics* (database), *http://dx.doi.org/10.1787/data-00004-en*.

OECD (2015), *CO_2 Emissions from Fuel Combustion 2015*, OECD Publishing, Paris, *http://dx.doi.org/10.1787/co2_fuel-2015-en.*

OECD (2014), *The Cost of Air Pollution: Health Impacts of Road Transport*, OECD Publishing, Paris, *http://dx.doi.org/10.1787/9789264210448-en.*

OECD/ECMT (2007), *Managing Urban Traffic Congestion*, OECD Publishing, Paris, *http://dx.doi.org/10.1787/9789282101506-en* .

Park W.H., J.G.M. Bullowa and N.M. Rosenbluth (1928), "The treatment of lobar pneumonia with refined specific antibacterial serum", *Journal of the American Medical Association*, Vol. 91/20, pp. 1503-1508.

Pickrell, D., D. Pace and J. Wishart (2014), *FHWA Travel Analysis Framework Development of VMT Forecasting Models for Use by the Federal Highway Administration*, John A. Volpe National Transportation Systems Center, Washtington, D.C.

Pickrell, D. and P. Schimek (1999), "Growth in Motor Vehicle Ownership and Use: Evidence from the Nationwide Personal Transportation Survey", *Journal of Transportation and Statistics*, Vol. 2/1, pp. 1-17.

Pirotte, A. and J.L. Madre (2012), “Déterminants du trafic des véhicules légers et élasticités : une approche spatiale sur données régionales françaises”, *Economie et statistique*, Vol. 457/1, pp. 141-159.

Puller, S.L. and L.A. Greening (1999), "Household adjustment to gasoline price change: an analysis using 9 years of US survey data", *Energy Economics*, Vol. 21/1, pp. 37-52.

Rentziou, A., K. Gkritza and R.R Souleyrette (2012), "VMT, energy consumption, and GHG emissions forecasting for passenger transportation", *Transportation Research Part A*, Vol. 46/2012, pp. 487-500.

Schimek, P. (1996), "Gasoline and Travel Demand Models Using Time Series and Cross-Section Data from United States", *Transportation Research Record*, Vol. 1558, pp. 83-89.

Sims, R. et al. (2014), "Transport", in Climate Change 2014: Mitigation of Climate Change. Contribution of Working Group III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change *(Edenhofer, O. et al. (eds.))*, Cambridge University Press, Cambridge, UK and New York, NY, USA, pp. 599-670.

Small, K.A. and K. Van Dender (2007), "Fuel Efficiency and Motor Vehicle Travel: The Declining Rebound Effect", *The Energy Journal*,Vol.28/1, pp. 25-51.

Sorrell, S. and J. Dimitropoulos (2008), "The rebound effect: Microeconomic definitions, limitations and extensions", *Ecological Economics*, Vol. 65/3, pp. 636-649.

Sorrell, S., J. Dimitropoulos and M. Sommerville (2009), "Empirical estimates of the direct rebound effect: A review", *Energy Policy*, Vol. 37/4, pp. 1356-1371.

Stanley, T.D. and H. Doucouliagos (2012), *Meta-Regression Analysis in Economics and Business*, Routledge, New York.

Stanley, T.D. and S.B. Jarrell (1989), "Meta-Regression Analysis: A Quantitative Method of Literature Surveys", *Journal of Economic Surveys*, Vol. 19/3, pp. 299–308.

Stapleton, L., S. Sorrell and T. Schwanen (2016), “Estimating direct rebound effects for personal automotive travel in Great Britain”, *Energy Economics*, Vol. 54, pp. 313–325.

Steren, A., O.D. Rubin and S. Rosenzweig (2016), “Assessing the rebound effect using a natural experiment setting: Evidence from the private transportation sector in Israel”. *Energy Policy*, Vol. 93, pp. 41–49.

Su, Q. (2015), "How does fuel economy of vehicles affect urban motor vehicle travel in the USA?", *Energy Efficiency*, Vol. 8/3, pp. 339-351.

Su, Q. (2012), "A quantile regression analysis of the rebound effect: Evidence from the 2009 National Household Transportation Survey in the United States", *Energy Policy*, Vol. 45/0, pp. 368-377.

Su, Q. (2011), "Induced motor vehicle travel from improved fuel efficiency and road expansion", *Energy* Policy, Vol. 39/11, pp. 7257-7264.

van Dender, K. and P. Crist (2011), "What Does Improved Fuel Economy Cost Consumers and What Does it Cost Taxpayers? Some illustrations", *International Transport Forum Discussion Papers*, No. 2011/16, OECD Publishing, Paris, *http://dx.doi.org/10.1787/5kg9mq471x7g-en*.

Van Houtven, G., J. Powers and S.K. Pattanayak (2007), "Valuing water quality improvements in the United States using meta-analysis: Is the glass half-full or half-empty for national policy analysis?", *Resource and Energy Economics*, Vol. 29/3, pp. 206-228.

Wang, T. and C. Chen (2014), "Impact of Fuel Price on Vehicle Miles Traveled (VMT): Do the Poor Respond in the Same Way as the Rich?", *Transportation*, Vol. 41/1, pp. 91-105.

Weber, S. and M. Farsi (2014), "Travel Distance and Fuel Efficiency: An Estimation of the Rebound Effect using Micro-Data in Switzerland", paper presented at the 7th International Workshop on Empirical Methods in Energy Economics, Zurich.

Weitzman, M. and D. Kruse (1990), “Profit Sharing and Productivity”, in A. Blinder (ed.), *Paying for Productivity*, Brookings Institution, Washington D.C., pp. 95-142.

West, J. et al. (2015), "Vehicle Miles (Not) Traveled: Why Fuel Economy Requirements Don’t Increase Household Driving", *NBER Working Paper 21194*, Washington, D.C.

Wheaton, W.C. (1982), "The Long-Run Structure of Transportation and Gasoline Demand", *The Bell Journal of Economics*, Vol. 13/2, pp. 439-454.

WHO (2013), "Global status report on road safety 2013", Global Health Observatory Data.

World Bank (2016), World Development Indicators (database), *http://databank.worldbank.org/data/reports.aspx?source=world-development-indicators*.

Yu, B., J. Zhang and A. Fujiwara (2016), “Who rebounds in the private transport sector? A comparative analysis between Beijing and Tokyo”, *Environment and Planning B: Planning and Design*, Vol. 43/3, pp. 561–579.

APPENDIX

Table A.1. List of primary empirical studies used in the analysis

Ajanovic and Haas (2012)	Gillingham and Munk-Nielsen (2015)	Liu (2011)
Ajanovic, Schipper & Haas (2012)	Gillingham et al. (2015)	Mannering (1983, 1986)
Barla et al. (2009)	Goldberg (1996, 1998)	Mannering and Winston (1985)
Bento et al. (2009)	Gonzalez and Marrero (2012)	Matiaske, Menges & Spiess (2012)
Bergel, Depire & Mutter (2002)	Greene (1992, 2012)	Mayo and Mathis (1988)
Cervero and Hansen (2002)	Greene and Hu (1984)	Mizobuchi (2008)
Chugh and Cropper (2014)	Greene, Kahn & Gibson (1999)	Munk-Nielsen (2015)
Concas (2012)	Greening et al. (1995)	Noland (2001)
Dargay (2004)	Hansen and Huang (1997)	Noland and Cowart (2000)
De Borger, Mulalic & Rouwendal (2016)	Haughton and Sarkar (1996)	Odeck and Johansen (2016)
De Jong (1996)	Hensher, Milthorp & Smith (1990)	Pickrell and Schimek (1999)
De Jong et al. (2009)	Hensher and Smith (1986)	Pirotte and Madre (2013)
D'Haultfoeuille, Givord & Boutin (2014)	Hymel and Small (2015)	Puller and Greening (1999)
Dillon, Saphores & Boarnet (2015)	Hymel, Small & van Dender (2010)	Rentziou, Gkritza & Souleyrette (2012)
Feng, Fullerton & Gan (2013)	Johansson and Schipper (1997)	Schimek (1996)
Ficano and Thompson (2015)	Jones (1993)	Small and Van Dender (2007)
Fridstrøm (1998)	Kemel, Collet & Hivert (2011)	Stapleton, Sorrel & Schwanen (2016)
Frondel, Martinez Flores & Vance (2016)	Knittel and Sandler (2010, 2011)	Steren, Rubin & Rosenzweig (2016)
Frondel, Peters & Vance (2008)	Lamonde (2007)	Su (2011, 2012, 2015)
Frondel, Ritter & Vance (2012)	Lee (2015)	Wang and Chen (2014)
Frondel and Vance (2009, 2011, 2013)	Leung (2015)	Weber and Farsi (2014)
Gately (1990)	Li, Linn & Muehlegger (2014)	Wheaton (1982)
Gillingham (2014)	Linn (2016)	Yu, Zhang & Fujiwara (2016)
Gillingham, Jenn & Azevedo (2015)		

Note: More than one study has been produced by Frondel and Vance, Greene, Mannering, and Su.

Table A.2. Summary statistics for studies estimating the elasticity of travel with respect to fuel efficiency

Primary study	Country	Data Years	N	Mean	Min	Max
De Borger, Mulalic & Rouwendal (2016)	Denmark	2001-2011	14	0.094	0.054	0.174
Dillon, Saphores & Boarnet (2015)	United States	2008-2009	3	0.019	0.004	0.045
Frondel, Peters & Vance (2008)	Germany	1997-2005	5	0.716	0.575	1.152
Frondel, Ritter & Vance (2012)	Germany	1997-2009	2	0.506	0.418	0.594
Frondel and Vance (2009)	Germany	1997-2006	2	0.517	0.515	0.518
Frondel and Vance (2013)	Germany	1997-2012	4	0.612	0.188	0.953
Gillingham and Munk-Nielsen (2015)	Denmark	1998-2011	2	-0.006	-0.035	0.023
Greene (2012)	United States	1966-2007	6	-0.019	-0.143	0.144
Greene and Hu (1984)	United States	1978-1981	24	0.345	0.119	0.479
Greene, Kahn & Gibson (1999)	United States	1979-1994	4	0.250	0.193	0.286
Hymel and Small (2015)	United States	1966-2009	1	-0.023	-0.023	-0.023
Linn (2016)	United States	2008-2009	34	0.348	0.103	0.793
Liu (2011)	United States	2000-2011	10	0.159	-0.292	0.369
Matiaske, Menges & Spiess (2012)	Germany	1998-2003	1	-0.032	-0.032	-0.032
Mizobuchi (2008)	Japan	2007	4	0.254	0.166	0.411
Munk-Nielsen (2015)	Denmark	1997-2006	2	0.499	0.279	0.718
Schimek (1996)	United States	1950-1994	2	0.130	0.050	0.210
Stapleton, Sorrel & Schwanen (2016)	United Kingdom	1969-2011	24	-0.134	-0.643	0.309
Steren, Rubin & Rosenzweig (2016)	Israel	2007-2011	3	0.355	0.129	0.535
Su (2015)	United States	2008	8	0.131	0.090	0.172
Wang and Chen (2014)	United States	2008-2009	5	0.100	-0.203	0.700
Weber and Farsi (2014)	Switzerland	2010	4	0.528	0.187	0.814
Wheaton (1982)	Cross-national	1972	3	0.074	0.057	0.103
Yu, Zhang & Fujiwara (2016)	Japan and China	2009	40	0.475	-0.411	1.329
All			207	0.266	-0.643	1.329

Table A.3. Summary statistics for studies estimating the elasticity of travel with respect to per unit fuel costs

Primary study	Country	Data Years	N	Mean	Min	Max
Ajanovic and Haas (2012)	6 EU countries	1970-2007	14	0.328	0.050	0.880
Ajanovic, Schipper & Haas (2012)	12 EU countries	1980-2007	2	0.290	0.160	0.420
Barla et al. (2009)	Canada	1990-2004	4	0.129	0.080	0.187
Bento et al. (2009)	United States	2001	1	0.340	0.340	0.340
Chugh and Cropper (2014)	India	2010	2	0.800	0.670	0.930
Concas (2012)	United States	1982-2005	6	0.582	0.086	1.453
Dargay (2004)	United Kingdom	1976-1995	10	0.131	0.090	0.180
De Jong (1996)	Netherlands	1992	1	0.320	0.320	0.320
De Jong et al. (2009)	Netherlands	2008	1	1.220	1.220	1.220
D'Haultfoeuille, Givord & Boutin (2014)	France	2003-2009	1	0.530	0.530	0.530
Feng, Fullerton & Gan (2013)	United States	1996-2000	10	0.054	0.024	0.117
Frondel, Peters & Vance (2008)	Germany	1997-2005	3	0.587	0.581	0.596
Frondel, Ritter & Vance (2012)	Germany	1997-2009	2	0.540	0.459	0.620
Frondel and Vance (2009)	Germany	1997-2006	2	0.506	0.490	0.521
Gately (1990)	United States	1966-1987	2	0.080	0.070	0.090
Gillingham, Jenn & Azevedo (2015)	United States	2000-2010	3	0.108	0.076	0.150
Gillingham and Munk-Nielsen (2015)	Denmark	1998-2011	6	0.477	0.298	0.866
Gillingham et al. (2015)	Denmark	1996-2009	2	0.542	0.419	0.665
Goldberg (1996, 1998)	United States	1984-1990	17	0.043	-0.280	0.240
Greene (1992)	United States	1967-1989	15	0.178	0.059	0.450
Greene (2012)	United States	1966-2007	4	0.108	0.035	0.204
Greene, Kahn & Gibson (1999)	United States	1979-1994	6	0.228	0.175	0.280
Greening et al. (1995)	United States	1990	17	0.298	0.133	0.574
Haughton and Sarkar (1996)	United States	1970-1991	13	0.195	0.074	0.580
Hensher, Milthorp & Smith (1990)	Australia	1981-1982	8	0.268	0.065	0.389
Hensher and Smith (1986)	Australia	1981-1982	6	0.203	0.092	0.311
Hymel and Small (2015)	United States	2000-2009	38	0.075	0.008	0.309
Hymel, Small & van Dender (2010)	United States	1966-2004	44	0.123	0.024	0.322
Johansson and Schipper (1997)	12 OECD countries	1973-1992	8	0.212	0.061	0.470
Jones (1993)	United States	1967-1990	14	0.161	0.108	0.313
Kemel, Collet & Hivert (2011)	France	1999-2007	2	0.369	0.278	0.460
Knittel and Sandler (2010, 2011)	United States	1998-2010	19	0.229	0.096	0.440

Table A.3. Summary statistics for studies estimating the elasticity of travel with respect to per unit fuel costs (cont.)

Primary study	Country	Data Years	N	Mean	Min	Max
Lamonde (2007)	Canada	1990-2004	9	0.192	0.080	0.569
Linn (2016)	United States	2008-2009	5	0.442	0.125	0.894
Liu (2011)	United States	2000-2001	10	0.289	0.026	0.867
Mannering (1986)	United States	1979-1980	8	0.255	0.105	0.543
Mannering and Winston (1985)	United States	1978-1980	20	0.210	0.004	0.911
Mayo and Mathis (1988)	United States	1958-1984	2	0.241	0.221	0.261
Munk-Nielsen (2015)	Denmark	1997-2006	7	0.362	0.158	0.744
Schimek (1996)	United States	1950-1994	6	0.185	0.050	0.410
Small and Van Dender (2007)	United States	1966-2001	12	0.138	0.022	0.340
Stapleton, Sorrel & Schwanen (2016)	United Kingdom	1969-2011	34	0.182	0.023	1.420
Su (2011)	United States	2001-2009	8	0.084	0.028	0.196
Su (2012)	United States	2008-2009	33	0.154	0.097	0.224
All			431	0.197	-0.28	1.453

Table A.4. Summary statistics for studies estimating the elasticity of travel with respect to fuel price

Primary study	Country	Data Years	N	Mean	Min	Max
Bergel, Depire & Mutter (2002)	France	1981-1999	8	0.173	0.081	0.249
Cervero and Hansen (2002)	United States	1976-1997	2	0.201	0.179	0.223
De Borger, Mulalic & Rouwendal (2016)	Denmark	2001-2011	13	0.554	-0.184	1.026
Dillon, Saphores & Boarnet (2015)	United States	2008-2009	3	0.132	0.066	0.171
Ficano and Thompson (2015)	United States	2008-2009	14	0.640	0.255	1.625
Fridstrøm (1998)	Norway	1973-1994	2	0.183	0.109	0.257
Frondel, Martinez Flores & Vance (2016)	Germany	2000-2014	6	0.607	0.314	1.420
Frondel, Peters & Vance (2008)	Germany	1997-2008	5	0.616	0.476	0.801
Frondel, Ritter & Vance (2012)	Germany	1997-2009	8	0.655	0.551	0.898
Frondel and Vance (2009)	Germany	1997-2006	2	0.467	0.406	0.528
Frondel and Vance (2011)	Germany	1997-2009	12	0.424	0.018	0.689
Frondel and Vance (2013)	Germany	1997-2012	4	0.498	0.438	0.573
Gillingham (2014)	United States	2001-2003	33	0.303	0.120	0.690
Gillingham, Jenn & Azevedo (2015)	United States	2000-2010	17	0.120	0.007	0.411
Gillingham and Munk-Nielsen (2015)	Denmark	1998-2011	51	0.354	0.228	0.866
Gonzalez and Marrero (2012)	Spain	1998-2006	18	0.287	-0.030	0.615
Greene (2012)	United States	1966-2007	6	0.107	0.004	0.299
Greene and Hu (1984)	United States	1978-1981	24	0.199	-0.001	0.517
Greene, Kahn and Gibson (1999)	United States	1979-1994	4	0.250	0.193	0.286
Hansen and Huang (1997)	United States	1973-1990	4	0.093	0.080	0.100
Hymel and Small (2015)	United States	1966-2009	1	0.054	0.054	0.054
Kemel, Collet & Hivert (2011)	France	1999-2007	2	0.230	0.200	0.260
Knittel and Sandler (2010, 2011)	United States	1998-2010	11	0.444	0.288	0.625
Lee (2015)	United States	2002-2011	6	0.060	0.046	0.068
Leung (2015)	United States	2008-2009	24	0.104	-0.033	0.265
Li, Linn & Muehlegger (2014)	United States	1995-2001	6	0.251	-0.108	0.497
Linn (2016)	United States	2008-2009	25	0.150	0.093	0.587
Liu (2011)	United States	2000-2011	7	1.328	0.974	1.686
Mannering (1983)	United States	1979	24	0.097	0.020	0.226
Matiaske, Menges & Spiess (2012)	Germany	1998-2003	1	0.295	0.295	0.295
Munk-Nielsen (2015)	Denmark	1997-2006	2	0.504	0.282	0.725

Table A.4. Summary statistics for studies estimating the elasticity of travel with respect to fuel price (cont.)

Primary study	Country	Data Years	N	Mean	Min	Max
Noland (2001)	United States	1984-1996	67	0.093	-0.409	0.365
Noland and Cowart (2000)	United States	1982-1996	10	0.015	-0.135	0.080
Odeck and Johansen (2016)	Norway	1980-2011	4	0.213	0.110	0.358
Pickrell and Schimek (1999)	United States	1995	6	0.147	0.040	0.340
Pirotte and Madre (2013)	France	1985-2007	8	0.108	0.090	0.139
Puller and Greening (1999)	United States	1980-1990	4	0.728	0.690	0.770
Rentziou, Gkritza & Souleyrette (2012)	United States	1998-2008	6	0.158	0.034	0.310
Schimek (1996)	United States	1950-1994	2	0.160	0.060	0.260
Stapleton, Sorrel & Schwanen (2016)	United Kingdom	1969-2011	31	0.130	-0.080	1.020
Steren, Rubin & Rosenzweig (2016)	Israel	2007-2011	1	0.661	0.661	0.661
Su (2015)	United States	2008	8	0.145	0.040	0.265
Wang and Chen (2014)	United States	2008-2009	5	0.241	0.094	0.406
Wheaton (1982)	Cross-national	1972	3	0.529	0.500	0.547
All			500	0.258	-0.409	1.686