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Does the Swiss Car Market Reward Fuel Efficient Cars? Evidence from Hedonic Pricing Regressions, a Regression Discontinuity Design, and Matching

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Does the Swiss Car Market Reward Fuel Efficient Cars? Evidence from Hedonic Pricing Regressions, a Regression Discontinuity Design, and Matching.

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Abstract

To correct market failures due to the presence of negative externalities associated with energy consumption, governments have adopted a variety of policies, including taxes, subsidies, regulations and standards, and information-based policies. For example, labels that clearly convey energy consumption rates, associated costs, and emissions of conventional pollutants and CO_2, have been devised and used in the last two decades in several countries.

In 2003, Switzerland introduced a system of fuel economy labels, based on grades ranging from A to G, where is A best and G is worst, to assist consumers in making decisions that improve the fleet's fuel economy and lower emissions. We use a dataset documenting all passenger cars approved for sale in Switzerland each year from 2000 to 2011 to answer three key research questions. First, what is the willingness to pay for fuel economy? Second, do Swiss drivers—or Swiss auto importers on their behalf—appear to do a one-to-one tradeoff between car purchase price and savings on fuel costs over the lifetime of the car? Third, does the label have an additional effect on price, all else the same, above and beyond that of fuel efficiency alone?

Hedonic pricing regressions that exploit the variation in fuel economy across make-models, and over time within make-models, suggest that there is a (modest) capitalization of fuel economy into car prices. The diesel premium, however, exceeds the future fuel cost savings made possible by diesel cars, even at zero discount rates. An alternate calculation suggests that the fuel economy premium is consistent with a very low discount rate (2.5%).

We use a sharp regression discontinuity design (RDD) based on the mechanism used by the Swiss Federal Office of Energy to assign cars to the fuel economy label to see if the label has an independent effect on price, above and beyond that of the fuel economy. The RDD approach estimates the effect to be 6-11%. To broaden the fuel economy range over which we assess the effect of the A label, we also deploy matching estimators, and find that the effect of an A label on car price is approximately 5%.

Keywords: Fuel economy; CO_2 emissions; Passenger vehicles; Hedonic pricing model; Matching Estimator; Regression Discontinuity Design; Fuel efficiency premium; Discounted future fuel costs.

JEL Classification: Q48 (Energy – Government Policy); Q53 (Air Pollution; Water Pollution; Noise; Hazardous Waste; Solid Waste; Recycling); Q54 (Climate; Natural Disasters; Global Warming).

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1. Introduction

To correct market failures due to the presence of negative externalities associated with energy consumption, governments have adopted a variety of policies, including taxes, subsidies, regulations and standards. In the case of passenger vehicles, which in developed countries account for some 20% of total carbon dioxide (CO_2) emissions, the effectiveness of these policies depends crucially on whether consumers value or misperceive the benefits of improved fuel efficiency (Anderson et al., 2011). Labels that clearly convey energy consumption rates, associated costs, and emissions of conventional pollutants and CO_2, have been devised and used in the last two decades in several countries. What we examine here is one such label program.

CO_2 emissions are one of the main causes of climate change (IPCC, 2007), and, like many other countries, Switzerland has committed to reduce its CO_2 emissions with respect to the 1990 baseline, but has found it difficult to meet its targets. In July 2013, the Swiss federal government announced that it had failed to meet its CO_2 emissions reductions goals for 2012, and raised the carbon tax on heating fuels (an important contributor to Switzerland's CO_2 emissions) by about two-thirds.[2]

A large proportion (around one third) of the overall CO_2 emissions in Switzerland arises from road traffic, especially passenger cars. The energy consumption and CO_2 emissions of new passenger cars in Switzerland are among the highest in Europe. In 2012, new cars sold in Switzerland emitted on average 151 grams of CO_2 per kilometer, a much higher rate than their counterparts in Germany (140 grams CO_2/km), France and Italy (less than 130 grams CO_2/km).

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[2] See http://www.bafu.admin.ch/klima/03449/12696/index.html?lang=de&msg-id=49576

Representatives of the automotive industry assert that the high purchasing power of the Swiss and the country's topography are in part responsible for the heavy fuel use on Swiss roads. Motor fuels are also slightly less expensive in Switzerland than in other European countries.

In 2003 the Swiss government introduced a system of energy efficiency labels that presumably assist in conveying information about the fuel consumption and CO_2 emissions from a car. This system places cars into seven energy efficiency categories, ranging from A (best) to G (worst), and displays each car's average fuel consumption in liters per 100 km, along with CO_2 emissions in grams per kilometer.[3] The fuel efficiency categories are calculated by a combination of absolute and relative fuel consumption per 100 km, where relative means fuel consumption per 100 km per unit of curb weight. The cutoffs for placement into one of the seven label groups are computed so that they divide the distribution of fuel economy of the cars approved for sale in Switzerland from the two previous years into even intervals.

The CO_2 emissions rate of a car is determined through tests, and the fuel economy is proportional to the CO_2 emissions rate, with the proportionality factor a function of the type of fuel. The label further compares the CO_2 emissions rate from this vehicle with the average of new cars sold in Switzerland, but, unlike the EPA economy labels in the US, does not display the cost of driving the vehicle, either on annual basis or for a specified distance. We note that information about the fuel economy of a vehicle was available to car buyers even before the establishment of the energy label system, as it was and is normally included in manufacturers' "spec sheets" and in the Swiss Touring Club's description of each car, which is widely available to the public. The label must be affixed to the vehicle prior to the sale, but is then removed and there is no visible display of the fuel economy class when the car is driven around.

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[3] In the US, the fuel economy of a vehicle is usually expressed in miles per gallon (MPG). A higher MPG rating means better fuel economy. Liters per 100 kilometers are thus the reciprocal and the metrics equivalent of miles per gallon. A lower liters-per-100-kilometers rating denotes better fuel economy.

In this paper we ask three research questions. First, what is the (marginal) willingness to pay (WTP) for fuel economy in the Swiss car market? Second, is there a one-to-one tradeoff between car purchase price and savings on fuel costs over the lifetime of the car? Third, does the label have an additional effect on price, all else the same, above and beyond that of fuel efficiency alone?

To answer these questions, we have assembled a dataset that lists all cars approved for sale in Switzerland in each year from 2000 to 2011, and reports manufacturer-suggested retail prices (MSRPs) and extensive information about the attribute of the vehicles. We also have information about the driving habits of the Swiss, as documented in the Mikrozensus Mobilität und Verkehr 2010. We use the hedonic price approach (Rosen, 1974) and regress (log) price on vehicle attributes, including fuel economy. Attention is restricted to passenger vehicles with maximum weight of 3,500 kilograms and up to nine passenger seats.

In this paper we exploit the variation in fuel economy within a make-model. To disentangle the effect of the label above and beyond that of the fuel economy, and other car characteristics with which it is strongly correlated, we use a regression discontinuity design (RDD). The RDD takes advantage of the exact rule used by the Swiss Federal Office of Energy when assigning a vehicle to the appropriate energy class. We perform a number of falsification tests and robustness checks, including several based on matching methods.

We believe that our research questions and findings (summarized below) are of interest for four reasons. First, with a population of about 7.5 million, a stock comprised of 4.2 million passenger vehicles, new cars sales around 300,000 units a year, and no domestic car manufacturing, Switzerland is a small car market that depends entirely on imports. Automakers are unlikely to modify their models especially for the Swiss market, although auto importers can select which models they import into Switzerland. An individual auto importer, however, has only limited ability to influence the Swiss Federal Office of Energy's label cutoffs, because these also depend on the fuel economy of the vehicles carried by the other importers, and collusion is unlikely.

Second, starting in the late 1990s, the European Union entered in voluntary agreements with the major automakers aimed at fuel economy improvements and CO_2 emissions reductions. Switzerland is not part of the European Union, but it pursued similar voluntary agreements with the auto importers and may have benefited from the major automakers' technological advances and efforts, even though these were probably intended for other countries with large car markets (e.g., Germany, France, Spain, Italy and the UK).[4]

Third, there has been relatively little research on the importance of fuel economy, systems of fuel economy labels and policies that shape a fleet's fuel economy in Europe.[5] To our knowledge, our analysis is the first to examine the effects of a system of fuel economy labels for cars. While slightly less expensive than in most neighboring countries, motor fuel prices are high in Switzerland compared to the US, so our study is in the context of relatively high fuel prices.

Empirical work about the fuel economy premium based on the hedonic approach is fraught with difficulties, due to the high collinearity between vehicle attributes and fuel economy (Atkinson and Halvorsen, 1984; Knittel, 2011) and the potential for omitted variable bias. Earlier research has found mixed evidence about the value of fuel economy (Goodman, 1983; Arguea and Hsiao, 1993; Nair and Espey, 2004; Witt, 1997). In addition to collinearity problems and

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[4] The voluntary agreement proved to be ineffective, and so in 2007 the European Union established regulations imposing corporate average CO_2 emissions limits on automakers, which were phased in starting in August 2012. Switzerland has adopted these regulations, which were also phased in starting in August 2012.

[5] Klier and Linn (2011, 2012) have investigated fuel economy improvements in major European countries and the US.

other data limitations, one possible reason for this is that the value of the fuel economy may have changed over time, perhaps because of changing consumer tastes (Murray and Sarantis, 1999; Matas and Raymond, 2009). More recent work has focused on how the fuel economy affects the price of a car when fuel prices are changing (Busse et al., 2013), finding that adjustments occur in the *prices* of used cars and in the *shares* of new cars.

In theory, if individuals do not derive utility directly from the fuel economy of their cars (which means that the fuel economy enters in their utility optimization problem only via the budget constraint), consumers should give equal weight to the price of a car and the discounted flow of future fuel costs. Nair and Espey (2004) use data on automobiles sold in the U.S. in 2001 and conclude that automobile buyers fully internalize fuel cost savings attributable to improved fuel economy at low discount rates. This result is in sharp contrast with Allcott and Wozny (2013), who, under plausible assumptions about discount rates and consumer forecasts of future fuel prices, find that only about 70% of future fuel costs is captured into the price of a car. Sallee et al. (2011) use a slightly different econometric approach and data on wholesale car purchases, concluding that the discounting is not quite as pronounced as in Allcott and Wozny. Consumer failure to consider future fuel costs is seen as an argument in favor of regulatory approaches over market-based instruments, such as fuel taxes (Williams and West, 2005; Bento et al., 2009; Anderson et al., 2011).

Fourth, there has been limited research on the effect of fuel- or energy-efficiency certification labels. Experience from other settings suggests that people value certified energy efficiency in homes, office buildings and home appliances (Brounen and Kok, 2011; Eichholtz et al., 2010; Houde, 2013), may attach different weight to different pieces of information about energy efficiency and energy savings (Newell and Siikamaki, 2013), and that they respond to social norms (Allcott, 2011), for example reducing their usage of electricity when they are told that they use more than their neighbors but increasing it slightly otherwise. Studies have also found that people are, or say that they are, willing to pay more for the environmentally friendly version of an otherwise identical good, such as electricity (Ethier et al., 2000; Kotchen and Moore, 2007; Kotchen, 2009; Jacobsen et al., 2012).

It is not clear if and how these findings can be extrapolated to a label system for cars. The purchase of homes and office spaces suffers from an information asymmetry problem (Gans, 2012), and electricity usage is notoriously difficult for consumers to monitor, since people use it now and pay for it later. This shouldn’t be the case with cars, since fuel economy information is posted and people pay for gas at the pump. Qualitative research, however, suggests that the fuel economy and fuel expenditures are often only a second-order factor when purchasing a car and in households’ budget decisions (Turrentine and Kurani, 2007), and the Swiss labels contain an implicit “social norm” message.

Briefly, we find that, all else the same, fuel economy *is* capitalized into car prices. One set of our hedonic regressions suggests that the fuel efficiency premium is greater than the future fuel costs; a slightly different specification suggests that the future costs are discounted at a very low discount rate. This is in contrast with recent results from the US. Even more important, the label has an effect on price above and beyond that of the continuous fuel economy measure, even when we control for the latter. Based on our regression discontinuity design, we find that qualifying for the A label has an effect on car price ranging from 6 to 11%, at least within a narrow interval around the threshold. The matching approach estimates this effect to be 5%.

It should be kept in mind that we have manufacturer-suggested retail prices, not prices from actual transactions. We have, however, no reason to believe that there should be any differences between them that are systematically related to fuel economy or emissions. Our results suggest that auto importers believe that consumers *are* willing to pay more for an otherwise identical good if it receives an environmental certification, and price cars accordingly.

Recent research has shown that when fuel economy standards or penalties are based on discrete classes ("notches"), producers "bunch up" at the fuel economy levels that allow them to (barely) meet fuel standards and avoid penalties, with little actual effect on overall fuel economy (Sallee and Slemrod, 2011; Ito and Sallee, 2013). Our work shows that suppliers will take advantage of these local discontinuities even in a context where the only requirement is the display of information about fuel economy and CO_2 emissions, and the suppliers themselves have no influence over the producers' design and manufacturing process.

The remainder of the paper is organized as follows. Section 2 provides institutional background on the Swiss fuel economy label system. Section 3 presents theoretical considerations. Section 4 presents the methods, section 5 the data and section 6 does basic checks of the appropriateness of the regression discontinuity design. Section 7 presents the results, and section 8 concludes.

2. Background

In 2003 the Swiss government implemented an energy label system for passenger cars to inform drivers about the different characteristics of a vehicle, including fuel efficiency and CO_2 emissions. The labeling system places each car in one of seven efficiency categories, from A to G, A being the most fuel efficient (see Figure 1). The use of A-G label classes, and their graphical depiction, are similar to the label system used throughout Europe for homes and electrical appliances. The system applies to (new) passenger cars with a maximum weight of

3,500 kg and a maximum of nine passenger seats. The energy label must be displayed on every new passenger car for sale (but is removed once the car is sold).

In addition to car make and model, fuel type, transmission, and curb weight, the label displays fuel consumption (in the vehicle's actual fuel and as a gasoline equivalent), CO_2 emissions, a comparison of this car's CO_2 emissions with the average for new cars sold in Switzerland, and energy efficiency category (A to G). Unlike the labels used in other countries or other settings, the Swiss labels do not report fuel costs per unit of distance or for the average driver over a year.

Fuel consumption is determined by applying the New European Driving Cycle (NEDC).[6] In the NEDC, passenger cars are run through a predetermined test cycle to assess pollution and CO_2 emissions rates. The fuel consumption of the car is calculated by dividing the measured CO_2 emissions by an emission factor specific for each fuel type.

Many energy labels for passenger cars in Europe, including those used in France and Denmark, are based on absolute fuel consumption. By contrast, the Swiss energy label is based on combining absolute and relative fuel consumption.[7] The notion behind this dual system is that a pure absolute system would award the best efficiency categories only to small passenger cars, whereas a relative system allows bigger cars to attain the best categories.

The first step towards this classification is to compute each vehicle's rating number (RN). In 2003, when the system was established, the *RN* was calculated by applying the formula:

$$RN = \frac{65400 \cdot V}{4000 + 9 \cdot G} \tag{1}$$

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[6] See http://www.unece.org/trans/main/wp29/wp29regs101-120.html.

[7] Germany, Spain and the Netherlands are examples of other countries with label systems based on relative fuel consumption. In the German system, fuel consumption is normalized by weight, whereas the Spanish system considers the vehicle's footprint (AEA, 2011).

where *V* is the fuel consumption of the vehicle in kilograms per 100 km (kg per 100 km) and *G* is the curb weight in kilogram (kg). Fuel consumption is estimated in kg per 100 km so that different fuel types like gasoline, diesel or natural gas are comparable.

In 2006 the energy label system for passenger cars was revised and the calculation of the rating number was changed to

$$RN = 7267 \cdot \frac{V}{600 + G^{0.9}} \tag{2}$$

This adjustment effectively increases the weight placed on absolute fuel consumption and decreases that placed on relative fuel consumption. As with the previous rating system, a lower number denotes a more fuel efficient vehicle.

The Swiss Federal Office of Energy (SFOE) creates the cutoffs for assigning a car to each of the seven efficiency classes (A-G) by gathering the RN figures from all new cars approved for sale in Switzerland in the two years prior to the reference date (November 30), sorting them in ascending order, and selecting the RN of the last car in the bottom seventh of this distribution as the boundary for category A.

The RN cutoffs are thus revised every two years. Over the years the energy efficiency of passenger vehicles has improved, with more and more cars making class A. Instead of creating new categories like A+ and A++ (as is the case with appliances like refrigerators and others), the boundaries of the efficiency categories were lowered every second year. With these adjustments, class A is awarded only to the bottom seventh of the distribution of the fuel efficiency in the Swiss fleet at the reference date.

The boundaries of the other categories were determined in such a way that they all have the same bandwidth. The bandwidth, BW, is computed as

(3) $$BW = \frac{RN_{AVG} - RN_{A|B}}{2.5}$$

where RN_{AVG} is the average rating number and $RN_{A|B}$ is the boundary between categories A and B. This formula for computing the bandwidth was applied from the onset of the system to 2011. The cutoffs for placement in class A and the average RN for each year from 2003 to 2011 are summarized in table 1.

At the end of 2011 there was a substantial revision of the RN formula and the calculation of the category boundaries. Besides changes in the label's layout, the ratio of relative to absolute fuel consumption measure changed from 40:60 to 30:70. In other words, the absolute measure is weighted more heavily in the new system.[8] The data used in this paper stop at 2011 and are not affected by these changes.

3. Theoretical Considerations

Much of the earlier literature on car purchases and driving behaviors, and on the effects of fuel economy standards or fuel taxes (e.g., Bento et al., 2009, or Allcott and Wozny, 2013), relies on a model where the individual derives utility from driving distance M and from the consumption of other goods, X. The fuel economy e of the vehicle driven by this individual enters in the utility optimization problem only via the budget constraint. In a highly simplified setting with a single period, the individual chooses X, $\mathbf{Z}$, e and M to maximize the utility function:

(4) $$U(X, \alpha(\mathbf{Z}) \cdot M)$$

subject to the budget constraint

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[8] In order to compare all fuel types (i.e. including alternative fuels and electric cars), the new system uses well-to-wheel consumption instead of tank-to-wheel consumption when calculating CO_2 emissions and the RN score. For more information see www.energieetikette.ch.

(5) $$y = X + p(\mathbf{Z}, e) + p_f \cdot e \cdot M,$$

where **Z** is a vector of car attributes, $p(\mathbf{Z},e)$ is the price of the vehicle from the hedonic price function, e is measured in liters per unit of distance, and p_f is the price of a liter of fuel.[9]

The first-order condition for the optimum spell out that the individual chooses a level of fuel economy such that the slope of the hedonic function with respect to fuel economy is just equal to the marginal saving in fuel costs. The marginal willingness to pay for fuel economy is thus exactly equal to the marginal savings in fuel costs.

Consider now a driver who cares for the fuel economy of his car, perhaps because he realizes that a poor fuel economy implies high CO_2 emissions and creates other externalities:

(6) $$U(X, \alpha(\mathbf{Z}) \cdot M, e),$$

with $U_e < 0$, i.e., disutility is experienced with a worse fuel economy.[10] At the optimal level of fuel economy, the consumer's marginal willingness to pay for fuel economy will be the sum of two components—the marginal saving in fuel costs, and the marginal utility of the fuel economy, converted into dollars (or CHF) through dividing it by the marginal utility of income λ:

(7) $$\frac{\partial p(\mathbf{Z}, e)}{\partial e} = -p_f \cdot M + \frac{1}{\lambda} U'_e .$$

In practice, it is reasonable to expect some drivers to be of the type with utility (4) and some others to be of the type with utility (6). To the extent that the latter type exists, a more or less sizable share of consumers will be willing to pay for a fuel-efficient car more than the mere savings in fuel costs made possible by that vehicle.

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[9] In this model, the marginal utility of driving depends on the other attributes of the vehicle.

[10] A similar model where e in the utility function is replaced by $E(e)$, the vehicle's CO_2 emissions rate, which is an increasing function of e, results in analogous first-order conditions. An alternate model replaces the CO2 emissions rates with the total CO_2 emissions from driving, which are equal to $E(e) \cdot M$, in which case the consumer can affect total emissions through the choice of the fuel economy *and* by adjusting his or her driving. For the sake of simplicity, all of these models ignore the possibility that the individual's utility might also depend on the fleet's overall fuel economy, or, on society's or all drivers' total CO_2 emissions. See Andreoni (1990), Kotchen and Moore (2007), and Jacobsen et al. (2009) for models that explicitly derive an individual's contribution to the public good.

4. Approach

A. Estimating the Fuel Economy Premium

To answer our first research question, we estimate hedonic pricing regressions. The hedonic pricing approach is well established and has been widely deployed since Rosen's seminal paper (1974), and we refer the reader to Bockstael and McConnell (2007) for a thorough exposition. We have the full list of passenger vehicles approved for sale in Switzerland from 2000 to 2011, complete with manufacturer-suggested retail prices and car characteristics.

Our identification strategy relies on comparing vehicles that are similar in all aspects but differ for their fuel efficiency. We exploit the variation in fuel economy across "trims" and trim-variants within a make-model.[11]

To illustrate, consider the BMW 3-Series. This make and model includes the BMW 316, 318, 320, 323, 325, 328, 330 and 335. There is considerable variation in fuel economy across these trims: The fuel consumption per 100 km ranges from 4.592 to 13.6 liters of gasoline-equivalent fuel, for an average of 8.04 and a standard deviation of 1.58.

For the BMW 325, for example, we have a total of 260 observations in our dataset, as the BMW 325 was first introduced in Switzerland in 2001 and has been available every year since. This type of car comes as a sedan, hatchback, coupe, or convertible; it is available with manual or automatic gear shift, with or without Steptronic (sports mode gear shift), front-wheel or "x-drive" (four-wheel drive), with different engine sizes, and diesel or gasoline engine. The price ranges from about CHF 50,000 to 75,000 (2011 CHF).

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[11] In general, car models are differentiated by the "trim" level, and additional differences exist across variants of the trims, but there is considerable disagreement and confusion on what constitutes a trim. In this paper, we denote as a trim the combination of engine type (fuel or gasoline), engine size, transmission, and body type (e.g., sedan). A diesel sedan BMW 325 would thus be a different trim than a gasoline sedan BWM 325. In this paper, the 325xi version of the latter is a trim-variant.

The fuel economy likewise changes from one BMW 325 trim-variant to the next and over time: In 2003 and later years, about 4% of the BMW 325s were placed in the A class, 25% in the B group, 18% in the C group, 15% in the D group, 28% in the E group, and 9% in the F group. Even holding the exact trim-variant of a make and model the same, the fuel economy may change over time, and/or the SFOE's cutoffs for placement in one or another other fuel economy class have changed over time.

We estimate the regression equation:

$$\ln P_{imt} = a_m + \tau_t + \beta \cdot DIESEL_{imt} + \gamma \cdot FE + \sum_{j=A}^{F} LABEL_{imt,j} \cdot \delta_j + \mathbf{x}_{imt}\boldsymbol{\lambda} + \varepsilon_{imt} \tag{8}$$

where *i* denotes the trim-variant (e.g., BMW 325i Steptronic), *m* the make and model (e.g., BMW 3-Series), and *t* the year. *P* is the price of the car, *DIESEL* a dummy for diesel injection engine, *FE* is a continuous measure of fuel economy (see below), $LABEL_j$ is a dummy taking on a value of one if the vehicle has been placed in the *j* fuel economy label group, and **x** is a vector of car characteristics thought to affect its price. These include weight, engine size, horsepower per unit of weight, dummies for the number of doors, body type (e.g. station wagon, convertible, coupe, SUV), manual or automatic transmission, all-wheel drive, and gasoline-powered and turbocharged (see table 2). Polynomials in weight and horsepower per unit of weight are included in hopes of soaking up any other vehicle characteristics that influence price but are not documented in our dataset.[12]

Equation (8) thus includes make-model fixed effects and year fixed effects. One advantage of including the make-model fixed effects is that they capture difficult-to-measure vehicle attributes (quality, reliability, design, reputation of the automaker, etc.). They also

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[12] For example, information about safety and crash tests is very limited: We have this information (provided by the Swiss Touring Club) for only 453 make-model-trim-variants out of the thousands in our main dataset. Obvious determinants of safety, such as airbags and ABS brakes, are present in 99% of the vehicles, which means that for lack of variation we cannot use these variables in our regressions.

mitigate the possible endogeneity between price and fuel economy, to the extent that this endogeneity is driven by make-model-specific unobservables that are approximately constant over time.[13] Equation (8) allows for diesel vehicles to be valued differently than their gasoline-powered counterparts—above and beyond the effect on price due to their respective fuel efficiencies. Hybrid, electric vehicles and ethanol-only cars are excluded. The model is estimated by least squares with make-model and year dummies.

We have a number of possible measures of fuel economy, or, to be precise, of its reciprocal—fuel consumption for a given distance. The first is the number of liters per 100 km,[14] converted into gasoline-equivalents (FUELEQUI).[15] The lower FUELEQUI, the better the fuel economy of the car. The second is FUELEQUI divided by the weight of the vehicle. The third is RN, the measure used by the Swiss Federal Office of Energy to rate the fuel economy of the vehicle, which is a weighted average of FUELEQUI and FUELEQUI per unit of weight (see section 2). The fourth measure combines fuel consumption for a given distance traveled with the price of the fuel, which changes over time and is different across gasoline and diesel (see Figure 2), to produce fuel cost per 100 km (expressed in 2011 CHF).

All of these four measures are strongly correlated with one another, so that, in practice, we include only one at a time in the regression. In addition, they all so highly correlated with the diesel dummy that restrictions must be imposed on the coefficients of equation (8) in order to obtain meaningful results.

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[13] The problem of endogeneity is often addressed through instrumental variable estimation where the instruments are the other manufacturers' average fuel economy for the same vehicle class, or the same manufacturer's fuel economy in other vehicle classes (Berry et al., 1995). We do not attempt that approach in this paper.

[14] This is based on combined city and highway fuel consumption.

[15] The gasoline-equivalent fuel consumption of a gasoline car is, of course, the same as its regular fuel consumption. With diesel cars, the gasoline equivalent is obtained by multiplying fuel consumption by 1.12. This procedure is justified by the notion that 1) diesel engines are more efficient than gasoline engines, and 2) diesel fuel has a higher calorific content than gasoline. If the diesel engine had to be replaced with an equivalent gasoline engine, it would take 1.12 liters of gasoline for each liter of diesel needed to drive the car for 100 km.

One caveat is in order. The dependent variable in our models is the log of manufacturer-suggested retail prices—not the price at which a particular vehicle was actually sold. Our hedonic price function is thus the hedonic price function based on the car manufacturers and importers' beliefs about the consumers' bid functions.

We run regression (8) i) for all models and all years, ii) by car-size groups (e.g., microcar to compact, up to mid-size, etc.) to account for different market segments, and iii) for different periods to check the stability of the results. We have annual sales figures for each make-model starting with 2005, and we so re-run our regressions using sales weights for 2005-2011.

B. Comparing the Fuel Economy Premium and Future Driving Costs

Standard economic theory (i.e, the multi-period version of equations (4) and (5)) posits that the fuel efficiency price premium should be equal to the discounted flow of savings on the fuel costs that can be realized by switching to a more fuel efficient car. Using information from the Swiss Mikrozensus Mobilität und Verkehr 2010, combined with simple assumptions about the future prices of motor fuels, we test whether this is the case in the Swiss car market—our second research question.

A car's fuel economy is perfectly internalized into the price if:

$$\Delta P \approx \sum_{t=1}^{L} \left(\frac{1}{1+d} \right)^{t} \cdot q_t \cdot \left[m_t^0 \cdot FE_0 \cdot p_t^0 - m_t^1 \cdot FE_1 \cdot p_t^1 \right], \tag{9}$$

where ΔP is the fuel efficiency price premium, q_t is the probability that the car survives to year t, m is the number of kilometers driven per year, the subscripts 0 and 1 denote the initial (higher) and final (lower and thus better) fuel consumption rate, respectively, and p is the expected price of fuel in year t. The term in brackets represents the savings on fuel costs in year t made possible by switching from a less to a more fuel efficient vehicle. Equation (9) is flexible, in that it allows for cars with better fuel economy to be driven more or less than the others.

C. Assessing the Effect of the Label: Regression Discontinuity

In principle, the effect of the label is estimated by including a set of label dummies in the right-hand side of equation (8), along with all other car attributes and a continuous measure of fuel economy. In practice, however, the labels and alternate measures of fuel economy are highly correlated, which makes it difficult to disentangle them from one another, and to separate their effects from those of other vehicle attributes (Atkinson and Halvorsen, 1984; Knittel, 2011). We circumvent this problem by taking advantage of the SFOE's rule within a regression discontinuity design framework.

Regression discontinuity designs can be applied to estimate the average treatment effect on the treated (see Angrist and Pischke, 2010) in situations where units receive a treatment only if a variable—the so-called forcing or driver variable—exceeds (or is less than) a specified threshold, and units are unable to manipulate it precisely (Lee and Lemieux, 2010). Within a narrow bandwidth around the threshold, units that barely qualify for the treatment are presumed to be very similar to those that just barely miss the cutoff, the treatment is regarded as good as randomly assigned, and any systematic difference in the dependent variable is attributed to the treatment itself (Lee and Lemieux, 2010).

Consider, for example, the treatment represented by assignment to the A label. The driver variable is RN, the measure used by SFOE to place vehicles in the seven energy classes (see equations (1) and (2)), and the cutoffs for class A during the study period are reported in table 2. A vehicle is assigned to label A if and only if RN is less than or equal to the cutoff, with no exceptions, which means that we have a sharp regression discontinuity (Imbens and Lemieux, 2008; Lee and Lemieux, 2010). Vehicles with an RN score greater than this cutoff, but below the cutoff for the C label, are placed in the B group.

To estimate the average treatment effect on the treated (ATT) of placement in group A we fit polynomial regressions in (*RN*-*T*), where *T* is the A-group cutoff value, within a narrow range of zero. We fit polynomials up to order three with interactions between the treatment (the A label) and the polynomial terms to allow for the shape of the local regression function to be different across the cutoff:

$$\begin{aligned} (10) \qquad & \ln P_i = a + b\cdot A_i + c\cdot(RN_i - T) + d\cdot A_i\cdot(RN_i - T) + \\ & + f\cdot(RN_i - T)^2 + g\cdot A_i\cdot(RN_i - T)^2 + k\cdot(RN_i - T)^3 + m\cdot A_i\cdot(RN_i - T)^3 + \eta_i. \end{aligned}$$

The treatment effect is thus *b*.

If *f*, *g*, *k* and *m* are all equal to zero, equation (10) is simplified to a local linear regression with a rectangular kernel (Lee and Lemieux, 2010). For comparison, we also fit local linear regressions with a triangular kernel (Hahn et al., 2001), where the ATT is computed as $\hat{a}^- - \hat{a}^+$, with

$$(11) \qquad (\hat{a}^-, \hat{b}^-) = \arg\min \sum_{i\in B^-} (\ln P_i - a - b\cdot(RN_i - T))^2 K\left(\frac{RN_i - T}{h}\right),$$

$$(12) \qquad (\hat{a}^+, \hat{b}^+) = \arg\min \sum_{i\in B^+} (\ln P_i - a - b\cdot(RN_i - T))^2 K\left(\frac{RN_i - T}{h}\right),$$

B- and B+ the selected bins to the left and right of the cutoff, respectively, *h* the bandwidth, and K( ) the kernel function. The triangular kernel assigns heavier weights to observations closer to the cutoff.

Regression discontinuity designs (RDDs) presume that the units (here, the individual vehicles and/or the auto importers who obtain approval to sell them in Switzerland) do not have full control over the forcing variables (and hence on whether they make the A group), and that in the vicinity of the cutoff the A label is as good as randomly assigned. To make sure that this assumption is reasonable in our sample, we check that, within the selected bandwidth, i) the driver variable is continuous across the cutoff, ii) the covariates are balanced across the cutoff, and iii) the covariates vary smoothly across the cutoff.

We estimate the ATT for the "A" label group, and repeat the procedure for the other labels as well. We expect the treatment effect to be smaller, or absent altogether, for labels B through F.

D. Matching

The RDD approach produces results that hold within a narrow "window" of the cutoff, and as such it is difficult to generalize or extrapolate results to a broader range of fuel economy levels. We check if an "A" label premium still exists over a broader range of fuel economy values using a matching estimation approach.

Matching is made possible by the fact that SFOE's rules allow vehicles with very different fuel economies to get the same label (A through G; see section 5). We restrict attention to cars in the A and B class, and attempt to identify the premium associated with making class A.[16] For each A-class vehicle, we will thus look for a match—a vehicle with the same continuous measure of fuel economy, and similar in other aspects, but that has received a B label—and

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[16] We limit ourselves to these two classes because, as reported in section 7 below, the regression discontinuity approaches finds little or no effect associated with earning a B or a C label.

compute the price differential between them.[17] Once these price differentials are averaged over all possible pairs of matched vehicles, we obtain an estimate of the average treatment effect on the treated of reaching the A status.

Formally, the matching estimator of the A-label ATT is

$$\gamma_A^{matching} = \sum_x \Delta_x P(X_i = x \mid A_i = 1), \tag{13}$$

where Δ_x denotes the price differentials for matched observations and $P(X_i = x \mid A_i = 1)$ denotes the mass probability function for the vector of car characteristics X_i from an A-label vehicle i (Angrist and Pischke, 2009, page 71). It is important that this procedure be implemented on the common support for the X characteristics for A- and B-label vehicles.

If the vehicle attributes X used to match vehicles were solely binary indicators (e.g., the diesel and automatic transmission dummies), then the ATT estimated using expression (13) would be consistent and asymptotically normally distributed. With continuous variables, however, Abadie and Imbens (2011) show that (13) is biased, and propose a regression-based bias correction. The bias-corrected estimator is asymptotically normal. We deploy their correction, since our matching variables are a mix of continuous and binary variables, and use the asymptotic variance derived in Abadie and Imbens (2006).

Another possible complication arises from the fact that the cars in our dataset are both part of a cluster (for example, there are many variants of the BMW 325, and a BMW 328 is closely related to a BMW 325; both are part of the BMW 3-Series make and model) and of a panel (the same trim-variant of the BMW 325 may be present in the dataset, with minor or major

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[17] Our matching algorithm minimizes the Mahalanobis distance. Propensity score matching is not possible here, because using the key attributes of a vehicle (fuel economy and weight) it is possible to predict perfectly if a vehicle receives the A label. This would violate the overlap assumption, namely that the probability of treatment is between zero and one for both control and treated vehicles (Heckman et al., 1998).

updates, in several years). This means that a car within the same cluster (from the same or a different year) or the same trim-variant from another year may serve as a match for any given A-label car.

If the observations in our dataset are truly independent, such matches do not pose any problems. If they are correlated within make-model or over the years, then one of the basic assumptions of the matching estimator would be violated.[18] For good measure, for each particular selection of matching variables we run our matching algorithm and estimation twice—with and without imposing the restriction that matches be with vehicles from the same year.

5. The Data

We obtained price and vehicle characteristics for all new cars approved for sale in Switzerland from the Touring Club of Switzerland (TCS) for each of the years from 2000 to 2011.[19] We verified emissions and fuel economy against the TARGA dataset supplied by the Federal Roads Office (FEDRO). For 2005 and later years, we also have new car registrations from the Motorfahrzeuginformationsystem (MOFIS) dataset—the national vehicle information system, which is compiled and maintained by FEDRO upon receipt of registration records from the cantons. New car registrations are generally judged to be best measure of new car sales. We use the make-model sales figures as weights in our regressions (see below). We use the Mikrozensus from 2010 to get estimates of the distance driven every year as function of age and other vehicle characteristics, and to estimate a car "life table."

Attention is restricted to gasoline and diesel cars. Other fuels account for less than half of one percent of the observations. Table 3 tallies observations by year. On average we have over

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[18] See Assumption 3 and 3' in Abadie and Imbens (2006, page 239).

[19] The TCS car list is published annually in a booklet and updated online on a monthly basis (see http://www.bfe.admin.ch/energieetikette/index.html?lang=en||www.energieetikette.ch).

4,200 cars per year, for a total of 51,206 observations in the original sample, and 50,226 when we drop hybrids, ethanol-85, natural gas and electric vehicles, and the few cars manufactured in Russia, Romania or India.

The analyses in this paper are based on a sample that further excludes the top 5% of the distribution FUELEQUI (12.1 liters per 100 km or more) and contains 45,730 observations. This accomplishes two goals: First, it removes sports and high-performance cars (e.g., Ferrari, Maserati, Lamborghini), high-status and extremely expensive cars (e.g., Rolls Royce or Bentley), and unusually high-guzzling vehicles (e.g., Hummer H3). Fuel economy is unlikely to be a factor when purchasing one of these vehicles. Second, it ensures a common FUELEQUI support for diesel and gasoline cars, which is important for our hedonic regressions (see figure 3).

Car imports into Switzerland are clearly dominated by the German automakers (table 4), with French cars a distant second. Table 5 displays the top selling makes in 2011, the last year in our sample, and the makes with the most numerous make-model-trim-variants in that year. Unsurprisingly, there is considerable overlapping between the two panels of table 5: The best-selling makes also bring many models to the Swiss car market.

Table 6.a displays descriptive statistics of our first-cut sample (no hybrids or other alternative fuels, no Russian, Romanian or Indian cars). The cleaned sample (after further excluding high-consumption cars) is summarized in table 6.b. The mean price is CHF 43,422 and the median price is about CHF 40,000. The second panel of table 6.b reports information about fuel efficiency. The shares of A-D vehicles are relatively even, with E and F cars accounting for smaller shares. The mean fuel consumption rate is 7.70 gasoline-equivalent liters per 100 km (about 30.55 miles per gallon). Turning to fuel consumption per 1,000 kg of car weight, the mean is 5.14 liters and the median is 5.

The third panel of table 6.b displays summary statistics about other attributes of the cars. Diesel vehicles account for 39% of the sample. The mean weight is 1512 kilograms, the average horsepower is 9.54 for every 100 kilograms of curb weight, and the average engine size is 2 liters. Weight, horsepower, and fuel economy are highly correlated: For example, the coefficient of correlation between engine size and liters per 100 km is 0.82, and that between the latter and weight is 0.67. The coefficient of correlation between log price and any one of these variables is 0.75 or higher, which suggests that they are excellent predictors of price.

It is of interest to examine how fuel efficiency and weight have evolved over our study period. Reducing weight is one possible way for automakers to improve the fuel economy; increasing vehicle weight while making little or no change to the fuel economy one possible way to attain a better fuel economy label class. As shown in table 7, in this sample the average car weight has slightly increased and then decreased over time in a fashion that does not suggest any particular strategic response to the changing cutoffs for the A label,[20] while fuel economy improved steadily.[21] No particular trends can be recognized for the average engine size. The share of diesel cars has dramatically increased over time—from 18% in 2000 to 44% in 2011.

Table 8 summarizes the fuel economy and other car characteristics for selected groups of cars. This table shows clearly that diesel cars on average have better absolute and relative fuel economy, and lower fuel costs per 100 km, despite the fact that in Switzerland Diesel fuel is more expensive than gasoline. Perhaps the most striking result is that in our sample A-label vehicles account for 50% of the diesel cars, but for only 5% of the gasoline cars. Smaller cars have better absolute fuel economy, but their relative fuel consumption is no better than that for larger cars, and so the average fuel consumption rate per 1,000 kg remains virtually the same

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[20] Ito and Sallee (2013) document "bunching" effects and increased car weight in Japan when the fuel efficiency standards, which are weight-specific and more lenient for heavier vehicles, were changed.

[21] This is in line with Europe-wide statistics based on sales. See European Environment Agency (2013).

when the sample includes mid- and full-size cars. Nevertheless, the share of A-label cars is higher among the smaller cars.

Figure 3 displays the distributions of FUELEQUI for diesel and gasoline vehicles, showing the former lies to the left of the latter. Figure 4 is crucial to understanding one of our strategies for identifying the effect of the A label, namely our matching approach: The distribution of fuel consumption of fuel costs shifts to the right as we go from A-label cars to B-label cars and less and less efficient vehicles, but it is possible for cars with the same fuel consumption or fuel costs per 100 km to have different labels. For example, the common FUELEQUI support for A- and B-group cars is between 4.6 and 10.752 gasoline-equivalent liters per 100 km, the common costper100km support for A and B cars is between CHF 6.58 and 16.12 per 100 km, and that for all labels is CHF 8.90 - 16.13 per 100 km.

6. Basic Checks for the Regression Discontinuity Design

Upon close examination of the distribution of RN, the variable used by SFOE to assign cars to the appropriate energy efficiency class, we adopt an initial bandwidth of ±0.5 from the A label cutoff. A total of 2,757 vehicles fall within this bandwidth.

Our first order of business is to make sure that there are no discontinuities in the density of the driver variable, RN, across the cutoff. Since the cutoffs were changed after 2004, and again in 2006, 2008 and 2010, we check the density of the driver variable separately for each of these time periods. The histograms displayed in Figure 5 suggest that there is a likely discontinuity at the cutoff in 2003, but that this is not the case with the other periods.

McCrary’s density-based test (McCrary, 2007) likewise suggests that RN is discontinuous at the cutoff in 2003 (see Figure 6), even though the test statistic rejects only marginally at the 10% level (test statistic -0.5835, standard error 0.3503, and z statistic 1.65). The test fails to reject the null of no discontinuity for the other pairs of years and for the pooled 2004-2011 sample (test statistic -0.0970, standard error 0.1103, t statistic 0.88; see figure 7). For this reason, we fit equation (10) to 2004 and later years.

Next, we check that the covariates are balanced across the cutoff within the selected bandwidth. Table 9 shows that vehicles to the left and right of the cutoff, which barely qualify for and barely miss class A, respectively, are very similar in terms of weight, horsepower by weight, engine size, and shares of two-doors and four-doors. Diesel, automatic, and smaller cars, however, are more abundant among the vehicles that barely qualified for the A label. The results are virtually the same if we choose a narrower bandwidth (±0.3 from the cutoff, for a total of 1,676 vehicles). This means that we must control for these variables when we run our local regression discontinuity regressions. The covariates appear to be smooth across the cutoff.

Figure 8 displays the average log price by (RN–T) bins, suggesting evidence of a discontinuity in prices at the threshold for class A and of a non-linear relationship between RN and log price away from the cutoff. The mean log price in the bin immediately to the left of the cutoff is statistically different at the 5% or better from that in the bin immediately to the right of the cutoff (t statistic 2.28; p value 0.011). We estimate the average treatment effect on log prices at exactly this threshold in the next section.

7. Results

A. The Fuel Economy Premium

Is there a fuel economy premium, and, if so, how large is it? We suspect that persons who are especially careful with fuel costs might choose a diesel car to start with, so, ideally, we would like to fit a variant of equation (8) that includes the diesel dummy, a continuous fuel economy measure, and an interaction term between fuel economy and the diesel dummy.

Unfortunately, the collinearity between these three variables is extreme (the pairwise correlation coefficients are around 0.90) and the results are implausible.[22] For this reason, we report in tables 10 and 11 the results of runs where we enter the diesel dummy and a continuous fuel economy measure—together or one at a time.

Table 10 displays results based on using FUELEQUI as the continuous measure of fuel economy. In all market segments, when both the diesel dummy and FUELEQUI are included in the model, the diesel coefficient is approximately 0.11. The coefficient on FUELEQUI is positive—the wrong sign—but small. Suppressing FUELEQUI results in diesel coefficients that are likewise stable across market segments and of the order of about 0.08 – 0.09.

At the median car price, which is CHF 40,481, the diesel premium is thus about CHF 3,591 (2011 CHF). Based on the distance driven per year by diesel cars,[23] and on the survival curve for diesel cars derived from the 2010 Mikrozensus,[24] we compute the survival-probability-adjusted fuel costs to be CHF 2,946 at zero discount rate, which is below the Diesel premium of CHF 3,591 (standard error [s.e.] 40.11). These calculations assume, as in Allcott and Wozny (2013) and Anderson et al. (2013), that fuel prices follow a random walk process, so that the best prediction for the next period's price is today's price.

If our assumptions about future fuel costs, and survival probabilities, are correct and identical to those of the auto importers, the finding above suggests that the higher price of a

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[22] For example, diesel cars would appear to be 20-30% more expensive than otherwise identical cars that run on gasoline.

[23] Using the 2010 Mikrozensus data, we regressed kilometers driven in the last 12 months on the age of the car and a diesel dummy. The model predicts that the distance driven declines with age, at a rate of 198 kilometers per year, and that diesel cars are driven on average 4600 km more per year than gasoline cars.

[24] This curve assumes that the probability of surviving the first three years is, for all practical purpose, one, and that of surviving the 25th year of age is zero. The probability of surviving the first four years is estimated to be 0.88, and that of surviving the first five is 0.70.

diesel car over its gasoline counterpart is only in part explained by the fuel costs savings. Either diesel vehicles have other desirable features that we haven't been able to account for, or auto importers are exploiting a possible overestimation of fuel savings on the part of consumers,[25] or the latter are willing to pay for fuel economy per se, as suggested by the theoretical model of equations (6) and (7).

Suppressing the diesel dummy and keeping FUELEQUI indicates that there *is* a fuel economy premium. The fuel economy premium does *not* vanish as we include larger cars in the sample or examine all cars, although it is stronger in the small car segment. Using the coefficients from the regressions with data from 2003 and later, the marginal effect is CHF 1,137.53 for all cars (s.e. 21.68) and CHF 1,210.68 for small cars (s.e. 29.88).

In table 11 we use replace FUELEQUI with costper100km as our measure of fuel efficiency. This measure is obtained by multiplying the quantity of fuel needed to cover 100 km (diesel or gasoline) by its price in 2011 CHF, and is attractive to us because of the greater "within" make-model variation than FUELEQUI and ease of interpretation. The estimation results are qualitatively similar to those from the regressions with FUELEQUI.

The coefficient on costper100km from the all-car regression indicates that the marginal effect of the fuel economy (based on the median price of the car) is about CHF 696 (s.e., 11.70). Switching from gasoline to diesel reduces the fuel cost per 100 km by CHF 2.2 on average: The model predicts that the corresponding increase in car price is CHF 1,531.82 (a 3.78% increase; the standard error around this estimate is 25.74). Clearly, this is much less than the diesel premium (CHF 3,591) directly inferred from the coefficient on the diesel dummy. If we compute the discounted flow of future fuel costs using our estimates of the distance driven by diesel cars

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[25] This point is also made by Breteau and Weber (2013) and Tonozzi (2007).

each year and of a car's survival curve (see footnotes 22 and 23), we find that it would take a discount rate of just 2.5% for the present value of the future fuel costs to be equal to CHF 1,532.

B. Does the Label Have An Additional Effect? Preliminary Analyses.

One important research question in this paper is whether the label assigned by SFOE to a vehicle affects its price above and beyond the effect of other vehicle attribute, including the continuous measure of fuel economy. Unfortunately, extreme collinearity prevents us from disentangling the effect of the continuous fuel consumption rate measure and diesel dummy from that of the label dummies.

On comparing the diesel and fuel consumption rate coefficients across the 2000-02 period with 2003 and later years (first and third panel of table 10), it would seem that the introduction of the label system has strengthened the effect of fuel consumption on price. Moreover, if we enter the label dummies in equation (8) and exclude all other measures of fuel consumption and the diesel dummy, the coefficients on the label dummies are positive and significant, and indicate that, all else the same, A-rated cars are priced about 7-8% higher than the omitted category (group G), B-label cars about 5% more, C-label cars about 3% more, and D-label cars 1-2% more. E- and F-rated cars are virtually undistinguishable from G-label cars.

C. Regression Discontinuity

The estimation results from the regression discontinuity approach indicate that qualifying for the A label has a positive and significant effect on price. In all regressions we control for covariates found to be unbalanced across the cutoff (diesel, car size and body type, automatic transmission and all-wheel-drive dummies). The local linear regression with triangular kernel estimates the ATT to be 0.0786 (t statistic 3.12) (an 8.17% increase in price) at the optimal bandwidth, which is found to be about 0.26.[26] The discontinuity in log price at the cutoff is apparent in figure 9.

The size of this effect is in agreement with our preferred estimates from the polynomial regressions—those from the quadratic regressions—which range from 0.0647 (t statistic 2.32) at a bandwidth of 0.4 to a 0.102 (t statistic 1.59) at a bandwidth of 0.1. The corresponding price increases are 6.7% to 10.7%. For a bandwidth of 0.3, which is approximately equal to the optimal one above, the estimated ATT is 0.0733 (t statistic 2.25) and the associated effect on price 7.6%. We plot the log price predicted by this model against (RN-T) in figure 10. As in figure 9, the discontinuity is apparent, as is the non-linearity of log price away from the cutoff.[27]

Additional sensitivity checks with respect to changing the bandwidth and the order of the polynomial are reported in table 12. They show that a local linear regression (with a rectangular kernel) provides an acceptable approximation to the quadratic regression at the smallest bandwidth, and yields a comparable ATT. The quality of this approximation worsens, and the effect on price vanishes, as the bandwidth is increased. By contrast, the cubic polynomial regression "struggles" at the lowest bandwidth but produces estimates of the ATT similar to, and somewhat larger than, that from the quadratic regression at the other bandwidths. Except for the 0.3 bandwidth, however, Wald-type tests of the null that the coefficients on the cubic terms are both zero either fail to reject the null, or reject it only marginally.[28]

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[26] Bandwidth selection implies a tradeoff between bias (which is reduced by shrinking the bandwidth) and efficiency (which is improved by increasing the bandwidth to retain more observations). Imbens and Kalynamaran (2012) derive the optimal bandwidth that minimizes the mean square error of the estimate of the ATT.

[27] We have changed the scale of the vertical axis relative to that used in Figure 10 to emphasize the non-linearities away from the cutoff for the A label.

[28] These Wald tests use the robust variance-covariance matrix of the estimated coefficients, instead of the conventional one.

The results are robust to trimming the bottom and top 1% prices from the sample of A and B cars that fall in the 0.5 bandwidth, and excluding various subsets of the covariates from the regressions. We also conducted two falsification tests. In the first, we considered an arbitrary point to the left of the A-label cutoff, namely the one at distance 0.25 from the cutoff, and treated it as a new cutoff (a "fake" one). As expected with a non-existing treatment, a local linear regression with triangular kernel resulted in an insignificant estimate of the associated ATT (-0.033, t stat -0.78). In the second, we created a "fake" treatment based on the A-label cutoff established in late 2011 and applied it to the data from 2004 to 2010, when this cutoff was obviously not in place. The estimated ATT is 0.02, with a t statistic of 0.69.

In Switzerland some cantons have recently reduced the registration fees for low-emissions, high-efficiency vehicles. In principle, the auto importers may try to exploit these discounts on the registration fees to mark up their A-label cars.[29] To see if this is the case, we repeated our RDD regressions using the data from 2004 to 2008, since the earliest cantonal registration tax reforms occur in that year or later, and then with the data from 2004 to 2009.[30] For the 2004-2008 sample, the RDD estimate of the ATT is 0.098 (t statistic 2.32), which implies that attaining the A label has a 10.32% effect on price. For the 2004-2009 sample, the ATT is 0.0695 (t statistic 2.31), which means that the A label increases the price by 7.20%. The size of these effects is similar to that from the full sample, implying that our results are probably not driven by favorable registration tax regimes.

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[29] On a related note, Langer and Miller (2013) warn that at times of rising fuel prices US automakers offer incentives towards the purchase of relatively fuel inefficient vehicles, and that failing to account for these incentives understates consumer demand for fuel economy.

[30] In 2008, only one out of 26 cantons had introduced a discount on the registration fee for low-emissions cars. In 2009, seven cantons had adopted reduced registration taxes for low-emissions cars. By 2012, 12 out 26 cantons had some such policies. The discounts on the registration fees were, and still are, generally very modest.

We also used the regression discontinuity approach to see if qualifying for a B label brings a price premium over a comparable car with a fuel consumption rate barely above the B label threshold. Visual inspection of the data suggested once again suggested an initial bandwidth of ±0.5 from the cutoff for the B label. We found weak evidence of a B-label premium: The ATT based on quadratic specifications and/or local linear regressions with triangular kernels is 0.03 – 0.04 (a 3 to 4% effect). With t statistics no greater than 1.14, however, this effect is never significant at the conventional levels.[31]

We used procedures similar to the one above to examine whether an effect on price exists when a car attains the C label, but the effect was usually less than 1%, and statistically insignificant at the conventional levels. For example, the local linear regression with triangular kernel produces an estimated ATT of -0.007, with a t statistic of -0.18.

D. Matching

The results of various runs of our matching estimation procedure are displayed in table 13. Here, the "treatment" is receiving an A label, so the sample is comprised of A- and B-label cars. We use Mahalanobis distance nearest-neighbor matching, with one match for each A-label car, and check the sensitivity of the results to the selection of the matching variables by starting with a base specification, adding further car characteristics, and then requiring exact matches for some of them.

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[31] We initially considered, but eventually ruled out, falsification tests based on assigning 2000-2002 cars to artificial A classes based on the 2003 A-label cutoff. In 2001 and 2002, the driver variable (RN minus the 2003 cutoff for the A label), is not smooth across the cutoff, which means that a regression discontinuity design shouldn't be applied to the data from these years—whether actual or based on a "fictional" assignment. This leaves us with an insufficient number of observations from 2000 (only 47) to conduct this falsification test.

The results in table 13 are based on the bias-adjusted procedure,[32] on FUELEQUI (gasoline-equivalent liters per 100 km) as our measure of fuel consumption rate, and on limiting the sample to observations with A and B labels on the common support for FUELEQUI.[33] We find that the ATT is about 5%, is strongly statistically significant, and is remarkably stable across specifications and to removing the restriction that matches should be with vehicles from the same year.[34]

In runs not reported, we also ran our matching procedures with costper100km (an alternate measure of fuel consumption that accounts for the price of fuel) in lieu of FUELEQUI. The ATTs from these runs are positively and statistically significant, but smaller: The effect of the A label on price is approximately 2.2% (t statistic 2.81).

8. Conclusions

We have used price and car characteristics data from the Swiss car market in 2000 – 2011 to answer three key questions about whether the fuel economy of a vehicle is capitalized into its price. We have exploited a dataset with a unique level of detail and multiple measures of a vehicle's fuel economy. Our hedonic pricing regressions suggest that fuel economy is capitalized into car prices. One specification finds that the fuel economy premium is even greater than the mere savings in fuel costs; another suggests that future fuel costs are discounted at a relatively low rate.

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[32] In separate runs we found that not correcting for the bias tends to overstate the ATT.

[33] We remind the reader that this common support is 4.6 - 10.752 gasoline-equivalent liters per 100 km. This also ensures a common support for the other continuous covariates, namely weight, engine size, and horsepower per unit of weight.

[34] About one third of the matches were with the same exact make-model-trim-variant of the vehicle from another year. Imposing the restriction that matches be with cars from the same year (which of course will not allow matching with the same exact vehicle) reduces the occurrence of matches with an extremely similar make-model-variant to less than 1% of the cases, with the same make-model to 12% of the cases, and with the same make to only 14.85% of the cases.

Collinearity between the continuous fuel economy measures, the diesel dummy and the Swiss label dummies do not allow us to identify whether the latter have any additional effect on prices. We circumvent this problem using a regression discontinuity design to see if there is a jump in price when a car qualifies for the A label. The approach focuses on a narrow bandwidth around the threshold set by the Swiss Federal Office of Energy for making the A label. Within this narrow bandwidth, vehicles that barely qualify are regarded as similar to those that barely missed the mark, the only difference being the "treatment" represented by the label. We find convincing evidence of a 6-11% increase in price when the threshold is crossed.

To improve the external validity of our estimates, we also use a matching estimator, which exploit the fact that in our dataset there are cars with the same fuel economy but different SFOE-assigned labels. This approach indicates that there is a 5% price premium associated with making the best efficiency class compared to B-label cars.

The jump in price is much smaller, or absent altogether, when the threshold for less desirable labels (B, C, etc.) is met. Taken together with the evidence for the A label from the matching approach, this suggests that auto importers believe that the public is willing to pay more for a car when it receives the A certification. That consumers appear to be willing to pay more for an otherwise identical good when it receives an "environmentally friendly" certification has been observed in other contexts (Kotchen, 2009; Jacobsen et al., 2012; Houde, 2013).

However, our case is different, because consumers seem to be ready to pay more for an otherwise identical "environmentally friendly" good (virtually the same fuel economy and CO_2 emissions) if it has a different label. While the auto importers had relatively little room for strategic responses in terms of types of cars put on the market—and our analyses preliminary to the regression discontinuity estimation confirm that this is so especially in and after 2004—it would seem that they were able to act strategically with respect to pricing.

In 2011, when 25.9% of all new cars sold were A-label cars, the total “mark-up” was of the order of CHF 152 million.[35] For vehicles that received rating scores very close to the requirement for the A label, this mark-up is even more pronounced (up to 11%), even though fuel economy and CO_2 emissions are practically unchanged across the cutoff. To illustrate, we calculate that for diesel cars within the 0.1 bandwidth around the cutoff for the A label, the fuel economy of cars that attain the A label implies savings in fuel costs of only CHF 76.80 over the lifetime of the car.[36] The CO_2 emissions rates of A and B cars within this bandwidth are likewise virtually the same (159.83 and 159.95 g CO_2/km, respectively), so that the implicit willingness to pay per ton of CO_2 emissions avoided over the lifetime of the car is CHF 105,923. Broadening the bandwidth to 0.2 from the cutoff implies CHF 3817 per ton of CO_2 emissions, and further increasing it to 0.5 implies a willingness to pay of CHF 3505 per ton of CO_2 emissions reductions.

We conclude that label systems based on discrete categories—while familiar to the public and relatively easy to implement administratively—engender incentives for the suppliers much like standards and penalties based on “notched” criteria (Sallee and Slemrod, 2011; Ito and Sallee, 2013). When design and production processes cannot be changed, as is the case here, the suppliers will simply turn to pricing.

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[35] We obtain this figure as the product of 294, 082 sales, times 25.9%, times the 5% price differential estimated using the matching approach, times CHF 40,000, the median price of a car.

[36] For simplicity, this calculation assumes that the discount rate is zero. The discounted total fuel costs savings would be even smaller if we had used a non-zero discount rate.

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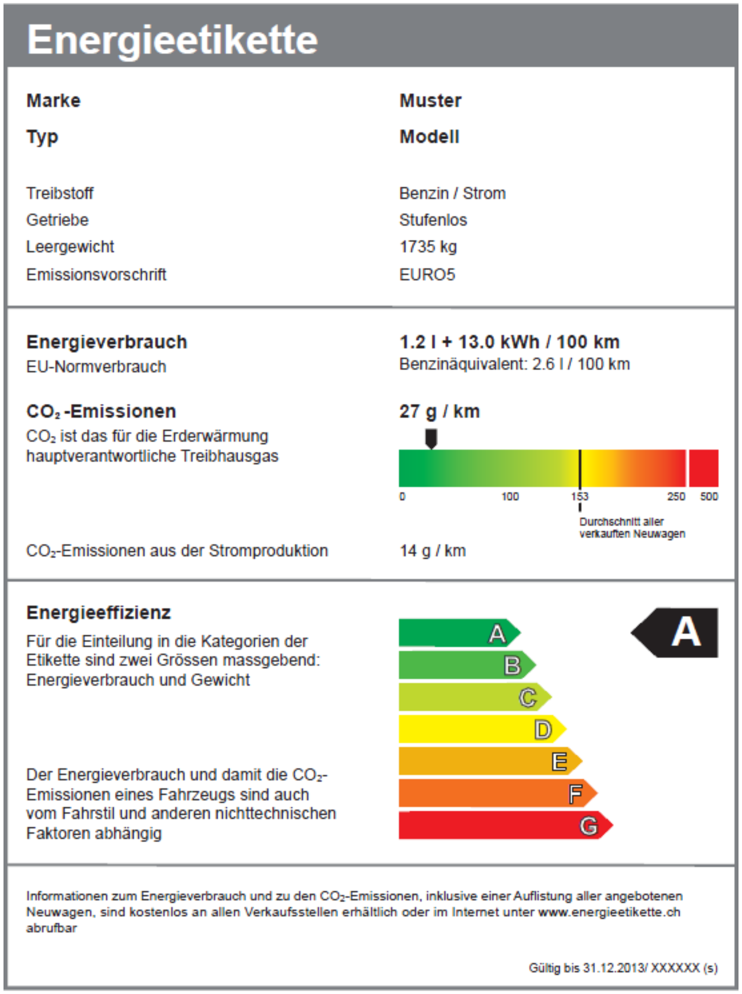
Figure 1. Example of the Swiss energy label for passenger cars. The example shown in this figure is a plug-in hybrid car.



Energieetikette

Marke	**Muster**
Typ	**Modell**
Treibstoff	Benzin / Strom
Getriebe	Stufenlos
Leergewicht	1735 kg
Emissionsvorschrift	EURO5

Energieverbrauch
EU-Normverbrauch

1.2 l + 13.0 kWh / 100 km
Benzinäquivalent: 2.6 l / 100 km

CO_2-Emissionen
CO_2 ist das für die Erderwärmung hauptverantwortliche Treibhausgas

27 g / km

CO_2-Emissionen aus der Stromproduktion

14 g / km

Energieeffizienz
Für die Einteilung in die Kategorien der Etikette sind zwei Grössen massgebend: Energieverbrauch und Gewicht

Der Energieverbrauch und damit die CO_2-Emissionen eines Fahrzeugs sind auch vom Fahrstil und anderen nichttechnischen Faktoren abhängig

Informationen zum Energieverbrauch und zu den CO_2-Emissionen, inklusive einer Auflistung aller angebotenen Neuwagen, sind kostenlos an allen Verkaufsstellen erhältlich oder im Internet unter www.energieetikette.ch abrufbar

Gültig bis 31.12.2013/ XXXXXX (s)

Figure 2. Fuel Prices in Switzerland, 2000-2011.

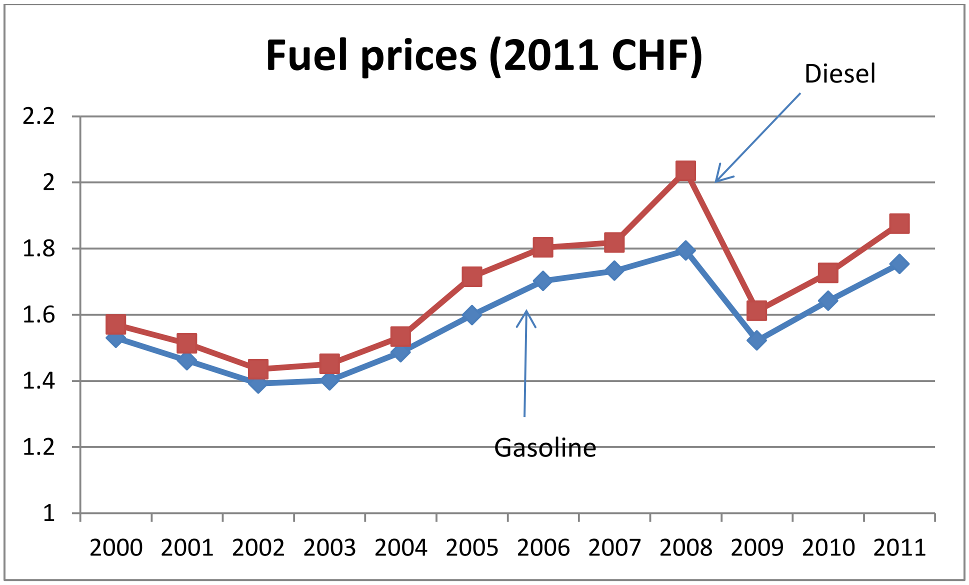


Figure 3. Distribution of fuel consumption (liters per 100 km in gasoline-equivalents) by type of fuel.

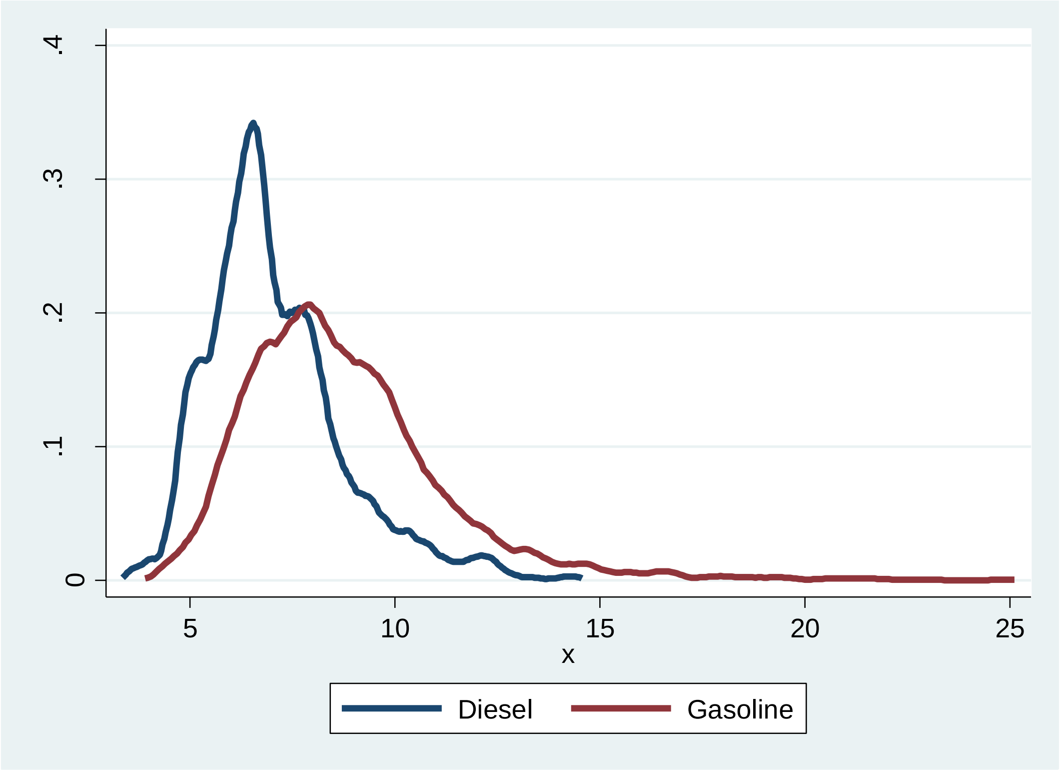
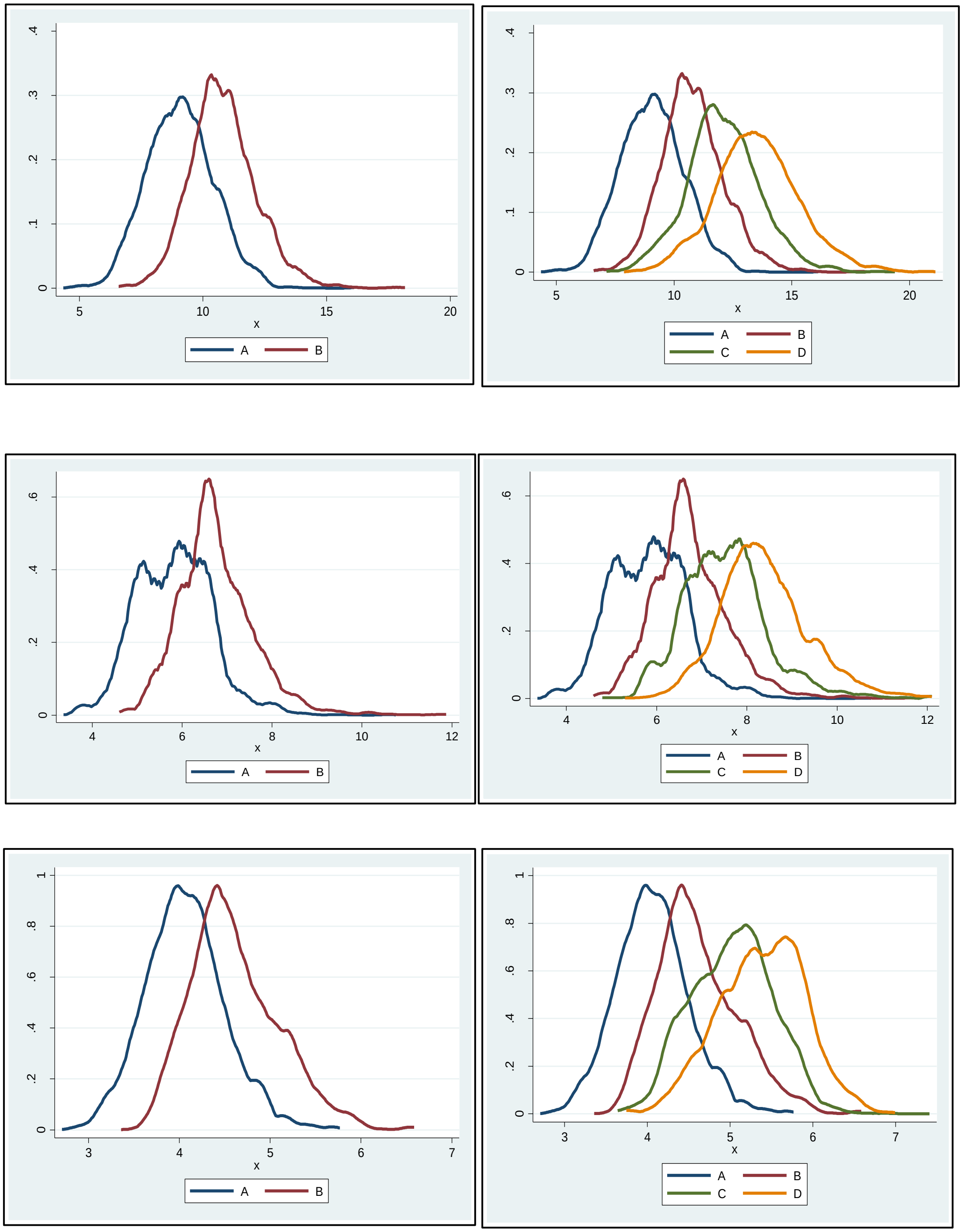


Figure 4. Distribution of various measures of fuel consumption by label class.



The first row displays densities for costper100km (cost per 100 km in 2011 CHF), the second for FUELEQUI (fuel in gasoline-equivalents per 100 km.), and the third for FUEL_WEIGHT (fuel per 100 km per 1000 kg of car weight).

Figure 5. Checks for a possible discontinuity of the driver variable around the cutoff. Bandwidth of ± 0.5 from the cutoff.

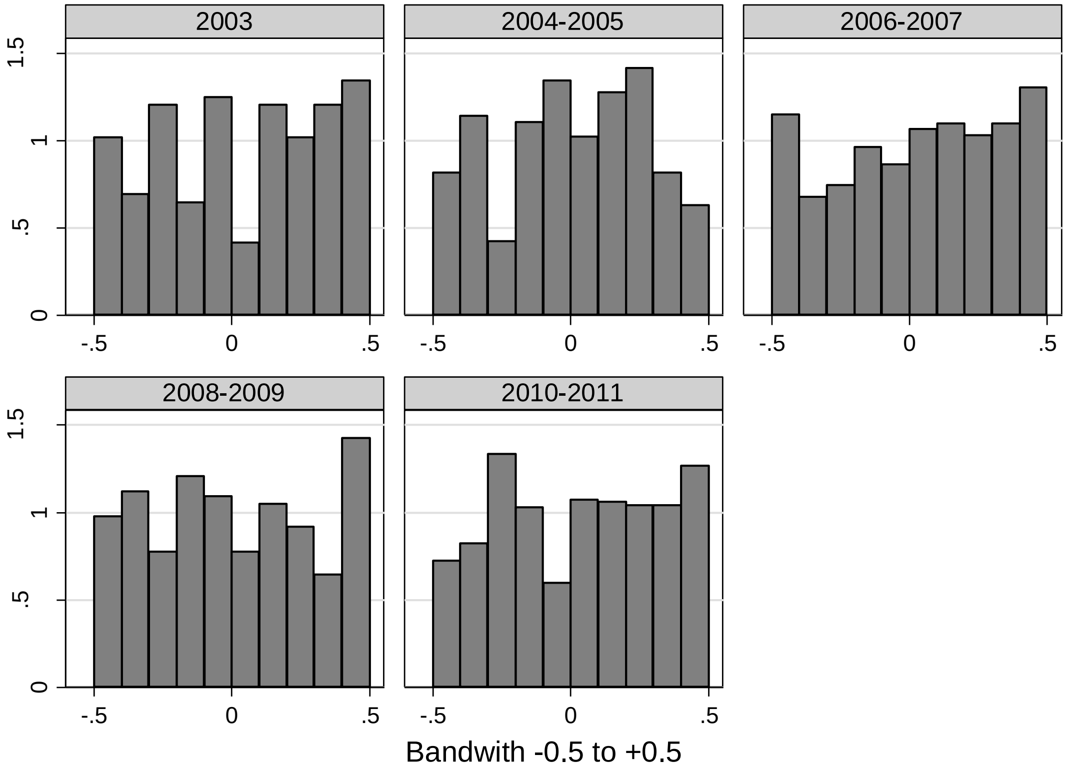


Figure 6. Density of the RN score at the cutoff in 2003.

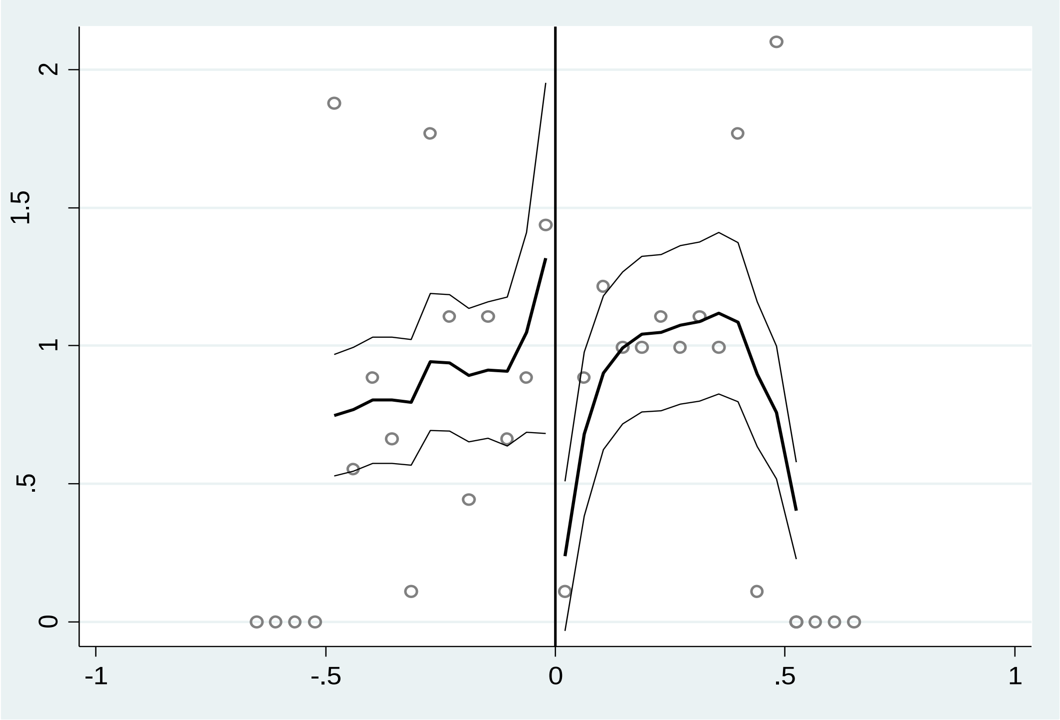


Figure 7. Density of the RN score at the cutoff, pooled 2004 and later years.

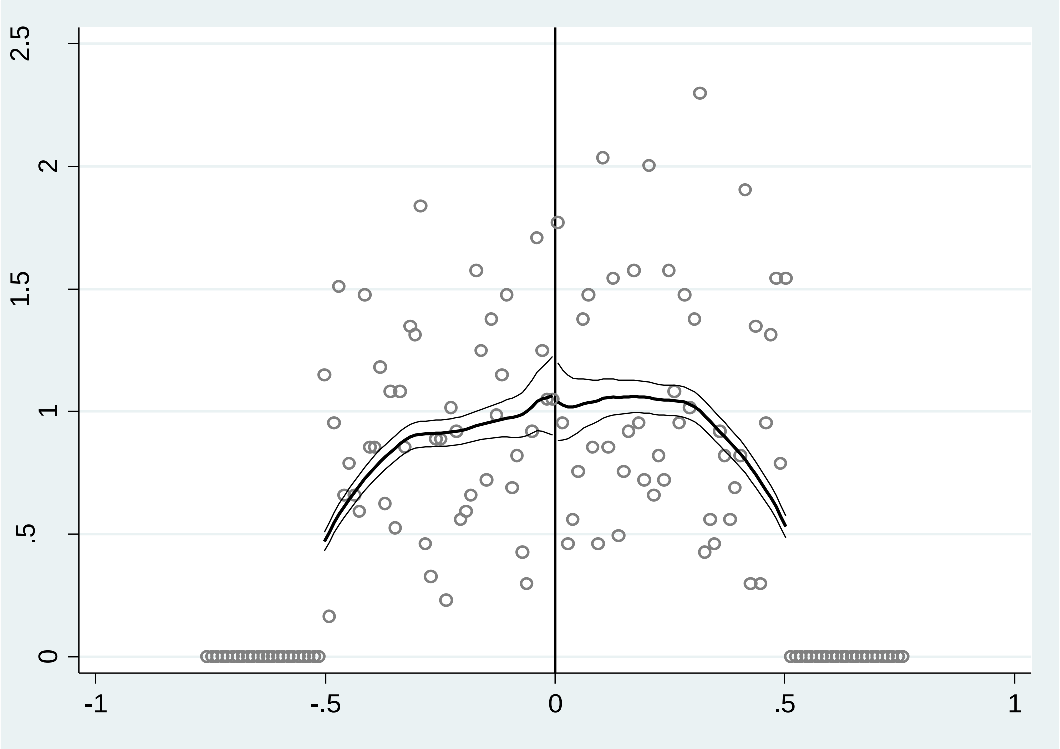


Figure 8. Evidence of regression discontinuity.

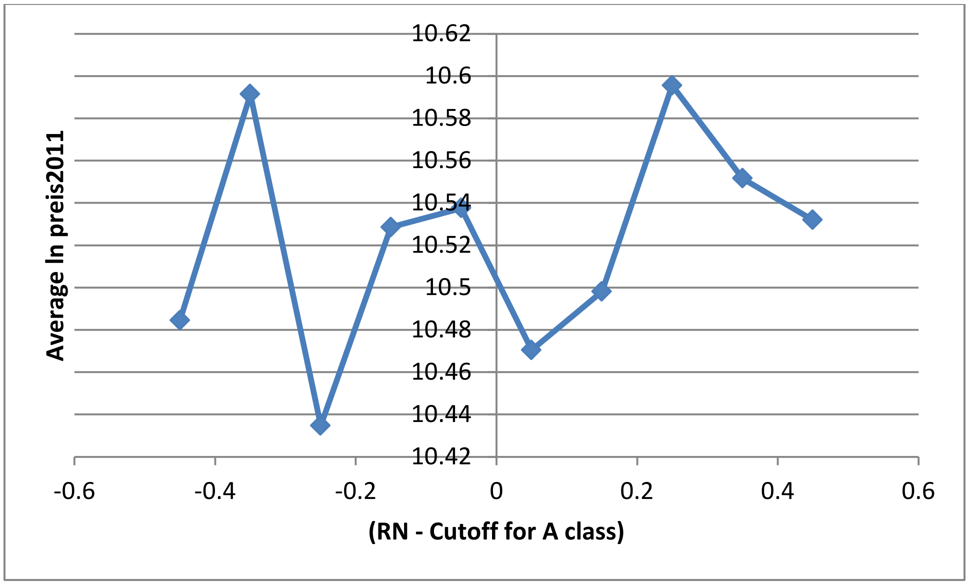


Figure 9. Regression discontinuity estimation: Local linear regression with triangular kernel, bandwidth ±0.5 from the cutoff. All years > 2003. The model controls for Diesel, car size, body type, number of doors, automatic transmission and AWD. The graph shows the log price predicted from the RDD regression model.

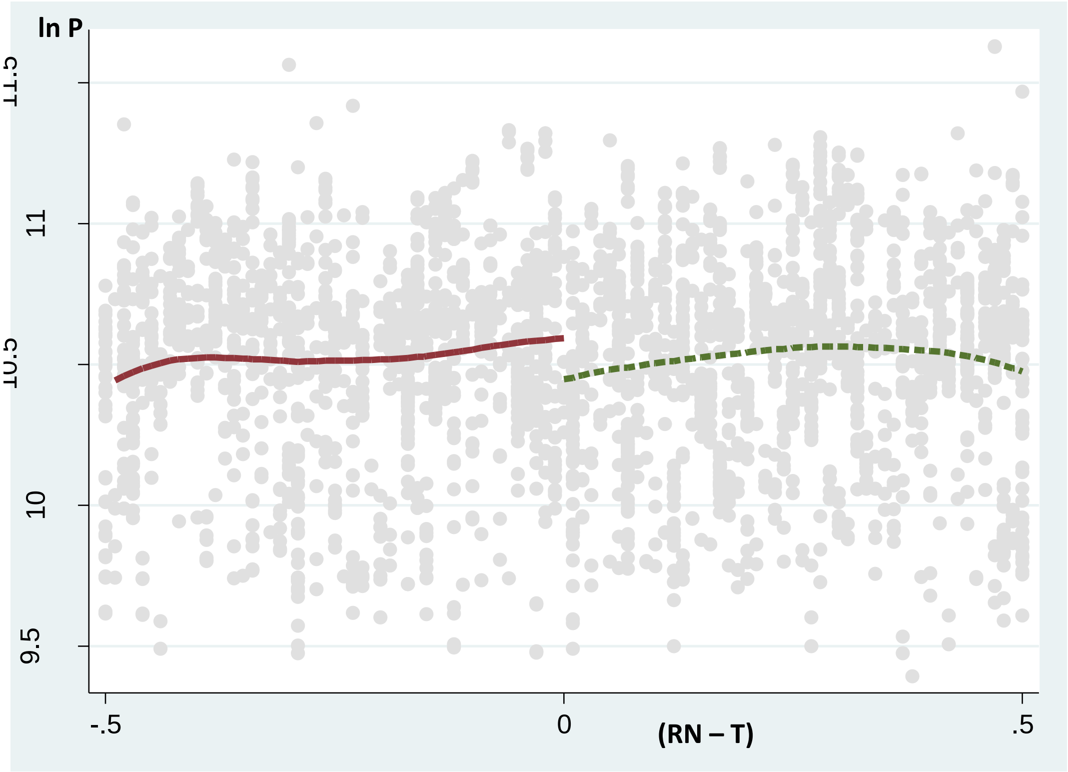


Figure 10. Regression discontinuity estimation: Results from regressions with quadratic terms in (RN-T), bandwidth ±0.3 from the cutoff. All years > 2003. The regression controls for Diesel fuel, car size, body type, number of doors, automatic transmission and AWD. The graph shows the log price predicted from the RDD regression model.

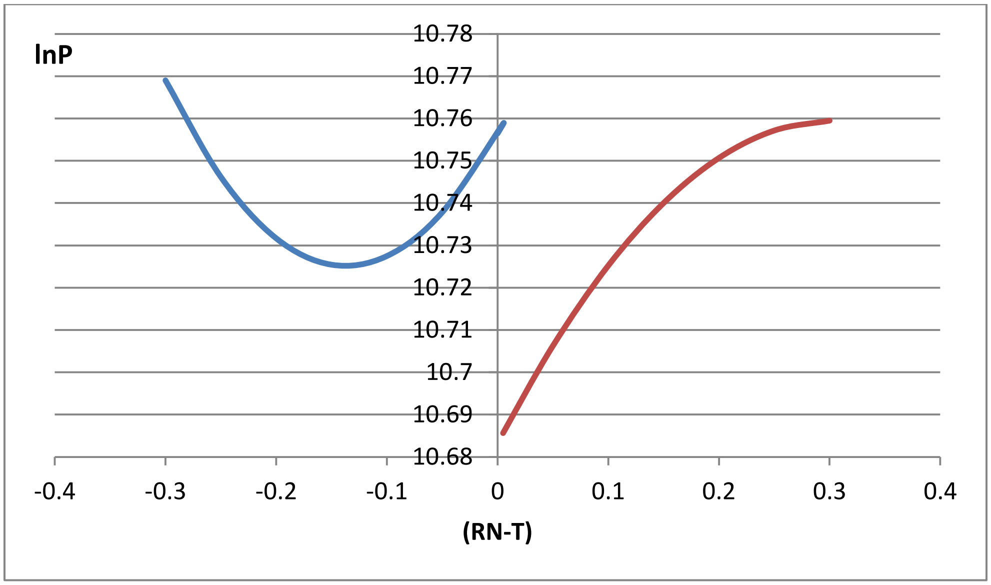


Table 1. Thresholds for placement in the A-class and average SFOE rating number score during the study period.

Year	A-label threshold	RN mean
2003	20.3	23.57
2004	18.9	23.04
2005	18.9	22.52
2006	26.54	32.59
2007	26.54	32.47
2008	26.22	31.87
2009	26.22	30.88
2010	24.72	29.34
2011	24.72	27.86

Table 2. Information and variables available in the annual car list compiled by the Touring Club of Switzerland.

variable	description and comments
preis	price of the car in current CHF
preis2011	price in 2011 CHF
marke	make (.e.g, BMW)
modell	model (e.g., BMW 3-Series)
ausfuehrung	trim-variant (e.g., BMW 328i Steptronic)
fahrzeugklasse	car class. Total of 10 classes based on size, body and performance (Cabriolet/Roadster; Coupé; Kleinwagen = subcompact; Luxusklasse = luxury class; Kleinstwagen = microcar; Mittelklasse = mid-size; Minivan; obereMittelklasse = full size; Gelandewagen = SUV; untereMittelklasse = compact)
karosserie	body (sedan, station wagon, SUV, convertible)
Horsepower	
hubraum	engine size in liters
leergewicht	curb weight in kg
getriebe	gear shift (automatic or manual)
vbrgesamt	fuel consumption in liters per 100 km
CO2 emissions rate	grams per kilometer
treibstoff	fuel (Diesel, Gasoline, Hybrid, Flexfuel, gas, plug-in electric)
energy label	from A (best fuel efficiency) to G (worst)
emission code	code for urban emissions (EURO-Norm)

Table 3. Number of vehicles approved for sale in Switzerland by year.

year	ALL	Only Diesel and gasoline; no Russian, Indian or Romanian cars	Further delete if exclusion =1*
2000	2,346	2,343	2,068
2001	2,435	2,427	2,166
2002	2,745	2,735	2,453
2003	3,732	3,699	3,340
2004	4,337	4,305	3,921
2005	4,953	4,918	4,501
2006	5,144	5,098	4,689
2007	4,960	4,864	4,415
2008	5,089	4,918	4,414
2009	5,060	4,856	4,424
2010	5,032	4,883	4,494
2011	5,373	5,180	4,845
Total	51,206	50,226	45,730

Table 4. Vehicles by "nationality" of auto manufacturer.

Country	ALL	Only Diesel and gasoline; no Russian, Indian or Romanian cars	Further delete if exclusion=1*
AUT	4	0	0
DE	20,672	20,523	18,264
ESP	1,269	1,269	1,269
FR	6,253	6,242	6,183
GB	1,443	1,439	879
IND	4	0	0
ITA	2,886	2,844	2,321
JAP	6,368	6,263	5,843
RUM	98	0	0
RUS	54	0	0
SKO	1,525	1,525	1,470
SWE	4,949	4,535	4,452
TCH	1,716	1,716	1,716
USA	3,965	3,870	3,333
Total	51,206	50,226	45,730

*: Vehicles with fuelequi>=12.10 (the 95th percentile of the distribution) are excluded.

Table 5. Top ten sellers and makes with the most numerous model-trim-variants in 2011. Source: MOFIS.

	marke	new car sales	Marke	number of model-trim-variants
1	VW	39,637	VW	580
2	AUDI	18,176	MERCEDES	458
3	RENAULT	18,168	VOLVO	420
4	FORD	18,002	AUDI	412
5	BMW	17,300	OPEL	306
6	SKODA	17,289	BMW	298
7	OPEL	15,737	SKODA	292
8	PEUGEOT	14,832	FORD	254
9	MERCEDES	13,757	SEAT	207
10	CITROEN	12,824	RENAULT	174

Table 6a. Descriptive Statistics of the Sample (only Diesel and gasoline cars; no Russian, Indian or Romanian cars). N=50226.

Variable	Description	Mean	Std. Dev.	Min	Max
preis2011	price in 2011 CHF	50,581.44	41621.24	10277.78	802626.3
lpreis2011	lnpreis 2011	10.67773	0.501554	9.23774	13.59564
A	A label	0.198861	0.399147	0	1
B	B label	0.159101	0.365774	0	1
C	C label	0.182236	0.386043	0	1
D	D label	0.160136	0.366736	0	1
E	E label	0.12388	0.329448	0	1
F	F label	0.081751	0.273987	0	1
fuelequi	fuel per 100 km in gasoline equivalent	8.116667	2.276267	3.36	25.1
fuel_weight	fuelequi/1000 kg	5.289139	1.096838	2.707998	16.42857
costper100km	fuel cost per 100 km (2011 CHF)	12.81019	3.764182	4.353632	38.21156
weight	weight (tons)	1.541212	0.305668	0.614	3.12
hp_weight	horsepower per 100 kg	10.18161	3.774058	4.38247	42.06186
engine_size	engine size in liters	2.162201	0.85388	0.599	8.285
Diesel	Diesel dummy	0.359256	0.479787	0	1
automatic	automatic transmission	0.379803	0.485343	0	1
AWD	all-wheel drive	0.169494	0.375191	0	1
benzineturbo	turbocharged and gasoline powered	0.034703	0.183029	0	1
Cabriolet	Convertible	0.054076	0.226169	0	1
SUV		0.094095	0.291963	0	1
Station_Wagon		0.213077	0.409486	0	1
Coupé		0.044479	0.206159	0	1
Van	Minivan	0.114463	0.318376	0	1
microcar		0.025704	0.158252	0	1
Subcompact		0.09726	0.296315	0	1
compact		0.214331	0.410362	0	1
midsize		0.250767	0.433459	0	1
fullsize		0.116513	0.320843	0	1
ttueren2	2-door	0.13272	0.339275	0	1
ttueren3	3-door	0.186179	0.389255	0	1
ttueren4	4-door	0.5973	0.490446	0	1

Table 6b. Descriptive Statistics of the Sample (only Diesel and gasoline cars; no Russian, Indian or Romanian cars; no exclusion=1*). N=45,730.

Variable	Description	Mean	Std. Dev.	Min	Max
preis2011	price in 2011 CHF	43421.98	18722.91	10277.78	270000
lpreis2011	lnpreis 2011	10.5962	0.404851	9.23774	12.50618
A	A label	0.217385	0.412471	0	1
B	B label	0.172272	0.377621	0	1
C	C label	0.197223	0.397906	0	1
D	D label	0.171157	0.37665	0	1
E	E label	0.126438	0.332346	0	1
F	F label	0.078001	0.268177	0	1
fuelequi	fuel per 100 km in gasoline equivalent	7.704944	1.702454	3.36	12.096
fuel_weight	fuelequi/1000 kg	5.140433	0.926224	2.707998	12.96552
costper100km	fuel cost per 100 km (2011 CHF)	12.14434	2.852291	4.353632	21.9799
weight	weight (tons)	1.512294	0.278073	0.665	2.81
hp_weight	horsepower per 100 kg	9.540745	2.616738	4.38247	41.6635
engine_size	engine size in liters	2.00221	0.577021	0.599	5.666
Diesel	Diesel dummy	0.385786	0.486786	0	1
automatic	automatic transmission	0.36066	0.480197	0	1
AWD	all-wheel drive	0.158255	0.364984	0	1
benzineturbo	turbocharged and gasoline powered	0.029259	0.168533	0	1
Cabriolet	Convertible	0.03302	0.178691	0	1
SUV		0.081609	0.273772	0	1
Station_Wagon		0.229937	0.420796	0	1
Coupé		0.021736	0.145823	0	1
Van	Minivan	0.121736	0.326985	0	1
microcar		0.028231	0.165634	0	1
subcompact		0.106823	0.308891	0	1
compact		0.234551	0.423722	0	1
midsize		0.273475	0.445747	0	1
fullsize		0.122283	0.327616	0	1
ttueren2	2-door	0.137131	0.343989	0	1
ttueren3	3-door	0.18946	0.391878	0	1
ttueren4	4-door	0.629281	0.483003	0	1

*: Vehicles with fuelequi>=12.10 (the 95th percentile of the distribution) are excluded.

Table 7. Car characteristics over the study period: Averages by year. Only Diesel or gasoline, no Russian, Indian or Romanian cars.

Year	Weight (tons)	Fuelequi (liters/100 km)	fuel_weight (liters/100 km per 100 kg)	engine_size (liters)	costper100km (2011 CHF)	Diesel (dummy)	A label (dummy)
2000	1.410	9.02	6.41	2.15	13.62	0.18	n/a
2001	1.427	8.86	6.22	2.16	12.79	0.20	n/a
2002	1.446	8.76	6.06	2.17	11.99	0.24	n/a
2003	1.499	8.51	5.70	2.14	11.70	0.30	0.22
2004	1.505	8.36	5.56	2.14	12.15	0.32	0.16
2005	1.526	8.27	5.42	2.16	13.05	0.35	0.21
2006	1.537	8.14	5.30	2.16	13.60	0.38	0.16
2007	1.616	8.31	5.15	2.22	14.08	0.39	0.17
2008	1.609	8.15	5.07	2.24	14.68	0.39	0.18
2009	1.599	7.89	4.93	2.20	11.76	0.42	0.24
2010	1.566	7.41	4.73	2.14	11.88	0.44	0.23
2011	1.571	7.04	4.49	2.08	12.12	0.44	0.33
all years	1.541	8.12	5.29	2.16	12.81	0.36	0.21

Table 8. Fuel economy and characteristics of cars by fuel type and size class. Only Diesel and gasoline cars; no Russian, Indian and Romanian cars; deleted exclusion=1.*

Measure	fuelequi	fuel_weight	costper100km	weight	A*	Diesel
Unit	liters/100km	liters/100km per 1000 kg	2011 CHF	thou. Kg	share	share
All	7.70	5.14	12.14	1.512	0.23	0.39
Diesel	7.00	4.33	10.79	1.614	0.49	1.00
Benzine	8.15	5.65	12.99	1.448	0.05	0.00
microcar, subcompact, compact	6.60	5.19	10.45	1.283	0.33	0.32
up to midsize	7.21	5.18	11.38	1.402	0.28	0.35
up to fullsize	7.46	5.17	11.77	1.451	0.26	0.36
A-label*	5.82	4.07	9.08	1.445	1.00	0.88
A- and B-label*	6.24	4.31	9.86	1.465	0.55	0.73
B label*	6.76	4.61	10.81	1.488	0.00	0.55

*: 2003 and later

*: Vehicles with fuelequi>=12.10 (the 95th percentile of the distribution) are excluded.

Table 9. Regression discontinuity design: Check of balance of the covariates across the cutoff for the A label. Mean of variables within the 0.5 bandwidth from the cutoff and t tests of the null of no difference across sample means.

	mean		
	A	B	t statistic
Weight	1.502	1.496	0.73
hp_weight	8.459	8.579	-1.81
engine_size	1.817	1.819	-0.11
Diesel	0.742	0.680	3.71
automatic	0.256	0.321	-3.88
two doors	0.039	0.058	-1.86
three doors	0.092	0.146	-4.54
four doors	0.136	0.146	-0.80
five doors	0.733	0.655	4.64
station wagon	0.295	0.212	5.24
micro car	0.054	0.034	2.45
subcompact	0.112	0.131	-1.58
compact	0.305	0.246	3.63
midsize	0.250	0.307	-3.49
AWD	0.063	0.080	-1.75

Table 10. Hedonic Regression Results: Summary of coefficients on fuel consumption rate and fuel type. The dependent variable is log price, and the regression includes make-model fixed effects, year fixed effects, control variables.

		2000-02		2000+		2003+		2005+		2005+ sales weighted	
		coeff	t stat	coeff	t stat	coeff	t stat	coeff	t stat	coeff	t stat
microcar, subcompact, compact[1]	Diesel	0.1314	14.13	0.1087	41.8	0.1057	37.4	0.1087	35.41	0.0995	29.05
	Fuelequi	0.0340	9.91	0.0108	7.66	0.0063	3.95	0.0074	4.20	0.0025	1.45
	Diesel	0.0682	9.84	0.0931	57.19	0.0967	57.36	0.0983	53.58	0.0957	43.87
	Fuelequi	0.0008	0.3	-0.0352	-37.87	-0.0415	-41.63	-0.0427	-38.37	-0.0364	-31.71
	Nobs	2125		15850		13725		11227		11031	
up to midsize[2]	Diesel	0.1396	21.8	0.11	62.06	0.1067	56.09	0.108	52.75	0.1002	47.21
	Fuelequi	0.0326	13.4	0.0153	16.72	0.0123	12.09	0.0134	11.95	0.0089	8.18
	Diesel	0.0771	17.17	0.0876	75.19	0.0889	73.37	0.0892	67.86	0.0877	59.49
	Fuelequi	-0.006	-3.39	-0.0277	-43.35	-0.0318	-46.23	-0.0322	-41.82	-0.028	-35.29
	Nobs	3900		28175		24275		19629		19396	
up to fullsize[3]	Diesel	0.1366	26.8	0.1129	74.17	0.1086	66.03	0.1096	61.73	0.1028	55.95
	Fuelequi	0.0336	17.57	0.0183	24.42	0.0154	17.93	0.0159	17.10	0.0121	13.07
	Diesel	0.072	19.18	0.0854	82.57	0.0864	79.40	0.0870	73.03	0.0858	65.89
	Fuelequi	-0.0034	-2.39	-0.0228	-46.83	-0.0267	-45.09	-0.0269	-40.26	-0.0246	-35.31
	Nobs	4879		34478		29599		23849		23577	
All[4]	Diesel	0.1408	31.73	0.1122	82.53	0.1072	73.05	0.1073	67.88	0.1044	65.13
	Fuelequi	0.032	19.57	0.0164	24.66	0.0126	16.85	0.013	15.64	0.013	15.94
	Diesel	0.0770	24.84	0.0878	93.68	0.0887	90.17	0.0891	83.17	0.0864	75.6
	Fuelequi	-0.0061	-5.12	-0.0237	-48.36	-0.0281	-52.52	-0.0287	-47.68	-0.0243	-39.48
	Nobs	6687		45730		39043		31782		31027	

[1]: fuelequi≥3.9 &fuelequi≤8.624

[2]: fuelequi≥3.9 &fuelequi≤10.192

[3]: fuelequi≥3.9 &fuelequi≤11.2

[4]: no fuelequi range restrictions

Table 11. Hedonic Regression Results: Summary of coefficients on fuel cost per 100 km and fuel type. The dependent variable is log price, and the regression includes make-model fixed effects, year fixed effects, control variables.

.		2000+		2003+		2005+		2005+ sales weighted	
		coeff	t stat	coeff	t stat	coeff	t stat	coeff	t stat
microcar, subcompact, compact[1]	Diesel	0.1108	37.81	0.1068	33.76	0.1104	32.45	0.0991	26.44
	costper100km	0.0063	7.24	0.0036	3.74	0.0044	4.20	0.0011	1.12
	Diesel	0.0932	57.19	0.0968	57.36	0.0983	53.58	0.0957	43.87
	costper100km	-0.0199	-42.16	-0.0231	-45.27	-0.0232	-41.22	-0.0198	-33.57
	Nobs	15850		13725		11227		11031	
up to midsize[2]	Diesel	0.1138	56.93	0.1091	51.26	0.1116	49.24	0.1023	44.18
	costper100km	0.0092	16.09	0.0071	11.53	0.0080	12.10	0.0052	8.18
	Diesel	0.0876	75.19	0.0889	73.37	0.0892	67.86	0.0877	59.49
	costper100km	-0.0173	-49.40	-0.019	-51.29	-0.0186	-45.82	-0.0165	-38.90
	nobs	28175		24275		19629		19396	
up to fullsize[3]	Diesel	0.1170	56.93	0.1111	60.91	0.1132	57.97	0.1055	52.64
	costper100km	0.0108	16.09	0.0086	16.86	0.0093	16.90	0.007	12.86
	Diesel	0.0854	75.19	0.0864	79.40	0.0870	73.03	0.0858	65.89
	costper100km	-0.0147	-49.40	-0.0163	-51.09	-0.0160	-45.10	-0.0148	-39.74
	nobs	34478		29599		23849		23577	
All[4]	Diesel	0.1150	75.52	0.1094	67.02	0.1105	63.54	0.1070	61.25
	costper100km	0.0093	22.42	0.0069	15.29	0.0074	15.32	0.0074	15.72
	Diesel	0.0880	93.83	0.0895	90.28	0.0896	83.07	0.0860	75.05
	costper100km	-0.0154	-57.34	-0.0172	-59.43	-0.0168	-52.83	-0.0145	-44.01
	nobs	45730		39043		31782		31027	

[1]: fuelequi≥3.9 &fuelequi≤8.624

[2]: fuelequi≥3.9 &fuelequi≤10.192

[3]: fuelequi≥3.9 &fuelequi≤11.2

[4]: no fuelequi range restrictions

Table 12. Regression Discontinuity Design: Estimation and Sensitivity to bandwidth selection and order of the polynomial. Dependent variable: log price. All models include the following covariates: Diesel, microcar, subcompact, compact, Van, SUV, automatic, AWD, ttueren2-ttueren4 (dummies for the number of doors). Robust t statistics.

		Linear		quadratic polynomial			cubic polynomial		
Bandwidth: ± of the cutoff	Nobs	effect of A coeff	t stat	effect of A coeff	t stat	Wald test statistic (p val)*	effect of A coeff	t stat	Wald test statistic (p val)**
0.1	531	0.0810	2.01	0.1023	1.59	11.020 (0.0004)	-0.0437	-0.45	8.247 (0.0162)
0.2	1135	0.0567	2.19	0.093	2.27	26.920 (less than 0.00001)	0.0755	1.28	5.185 (0.0748)
0.3	1676	0.0355	1.73	0.0733	2.25	3.350 (0.1837)	0.1189	2.61	32.260 (less than 0.00001)
0.4	2184	0.0244	1.36	0.0647	2.32	5.340 (0.0692)	0.0821	2.11	0.575 (0.7501)
0.5	2757	0.0049	0.31	0.0412	1.68	7.419 (0.0245)	0.085	2.50	4.669 (0.0954)

*: Wald test of the null that the null that the coefficients on the two quadratic terms (*f* and *g* in equation (10)) are zero. The statistic is based on the robust variance covariance matrix.

**: Wald test of the null that the coefficients on the two cubic terms (*k* and *m* in equation (10)) are zero. The statistic is based on the robust variance covariance matrix.

Table 13. Matching estimation. Dependent variable: log price. Sample: A- and B-label cars (n=15,821). Common support on fuelequi (4.6 – 10.752 liters per 100 km). Bias-adjusted estimation.

run	Effect of A label: ATT	t stat.	match by…	exact match by…	year-by-year match
1	0.0481	8.81	fuelequi, weight, engine_size, hp_weight, $doors		yes
2	0.0587	14.55	fuelequi, weight, engine_size, hp_weight, $doors, automatic, microcar, subcompact, compact, midsize, fullsize		yes
3	0.0614	15.05	fuelequi, weight, engine_size, hp_weight, $doors, automatic, microcar, subcompact, compact, midsize, fullsize, benzineturbo		yes
4	0.0491	9.88	fuelequi, weight, engine_size, hp_weight, $doors, automatic, AWD, microcar, subcompact, compact, midsize, fullsize, benzineturbo, Diesel		yes
5	0.0433	7.52	fuelequi, weight, engine_size, hp_weight, $doors, automatic, AWD, microcar, subcompact, compact, midsize, fullsize, benzineturbo	Diesel	yes
6	0.0471	7.72	fuelequi, weight, engine_size, hp_weight, $doors, automatic, AWD, benzineturbo	Diesel, microcar, subcompact, compact, midsize, fullsize	yes
7	0.0467	7.75	fuelequi, weight, engine_size, hp_weight, $doors, automatic, AWD, benzineturbo, Cabriolet, Coupe, SUV	Diesel, microcar, subcompact, compact, midsize, fullsize	yes
8	0.0564	8.2	fuelequi, weight, engine_size, hp_weight, $doors, Cabriolet, Coupe, SUV	Diesel, microcar, subcompact, compact, midsize, fullsize	no

$doors denotes a set of dummies for the number of doors.