What is the Effect of Fuel Efficiency Information on Car Prices? Evidence from Switzerland

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ABSTRACT

Inadequate information is often identified as a potential cause for the so-called "energy efficiency gap," i.e., the sluggish pace of investment in energy efficiency technologies, which potentially affects a wide variety of energy-using goods, including road vehicles. To improve the fuel economy of vehicles, in 2003 Switzerland introduced a system of fuel economy and CO_2 emissions labels for new passenger cars, based on grades from A (best) to G (worst). We have data for all cars approved for sale in Switzerland from 2000 to 2011. Hedonic regressions suggest that there *is* a fuel-economy premium, but do not allow us to identify whether the fuel economy label has an additional effect on car price, above and beyond the effect of fuel economy. To circumvent this problem, we turn to a sharp regression discontinuity design based on the mechanism used by the government to assign cars to the fuel economy label, which estimates the effect of the A label on price to be 6–11%. Matching estimators find this effect to be 5%.

Keywords: Fuel economy, CO_2 emissions, Passenger vehicles, Hedonic pricing model, Matching estimator, Regression discontinuity design, Fuel efficiency premium

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1. INTRODUCTION

There is considerable debate in academic and policy circles about the existence, extent and causes of the so-called "energy efficiency gap," namely the sluggish pace at which energy-efficient technologies are adopted (Jaffe and Stavins, 1994; Hassett and Metcalfe, 1995; Golove and Eto, 1996; Allcott and Greenstone, 2012). A wide variety of energy-using goods, such home appliances, buildings, machinery and vehicles, are potentially affected. Possible remedies to correct the negative externalities associated with excessive energy consumption include taxes, subsidies, regulations and standards, and programs that provide or reinforce information about the energy efficiency of these goods (Gillingham et al., 2009).

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.,

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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.

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). 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 for new cars 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.[1] The fuel efficiency categories are based on 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 this "composite" fuel economy of the cars approved for sale in Switzerland from the two previous years into even intervals.

The label itself summarizes the car's fuel type, fuel economy, and CO_2 emissions rates, and compares the latter with the average of new cars sold in Switzerland, but does not display an estimate of the fuel cost, either on an annual basis or for a specified distance. 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.

In this paper we ask two key research questions. First, is a vehicle's fuel economy capitalized into its price? Second, does the label have an additional effect on price, all else the same, above and beyond that of the fuel efficiency alone? Evidence of such an effect is potentially consistent with a number of possible explanations, including that some consumers experience utility directly from their vehicles' fuel economy or low emissions,[2] or that the additional information from the label helps consumers reduce uncertainty about true fuel economy and/or lowers search efforts (Sallee, 2013; Houde, 2014a).

Our analysis is based on 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 attributes of the vehicles. Attention is restricted to new passenger

1. 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 equivalent in metrics, of miles per gallon. A lower liters-per-100-kilometers rating denotes better fuel economy.

2. Assuming that a consumer derives utility from consumption goods, miles driven and fuel economy per se, and that the budget constraint states that income must be spent on consumption goods, car purchase price and fuel costs (which depend on miles driven, the fuel economy of the car, and the price of motor fuel), it is straightforward to show that the willingness to pay for a marginal change in fuel economy is the sum of two components—the marginal saving on fuel costs, and the value of the utility associated with the marginal unit of fuel economy. Most empirical work, however, assumes that individuals do not derive utility from fuel efficiency per se (see, for example, Allcott and Wozny, 2014).

vehicles with maximum weight of 3,500 kilograms and up to nine passenger seats. 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 (SFOE) to assign 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 8 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.[3]

Third, there is growing interest in assessing policies that shape a fleet's fuel economy in Europe, but most research in this area has focused on tax instruments (Mabit, 2008; Clerides and Zachariadis, 2008; Adamou et al., 2014; Klier and Linn, 2011, 2012; D'Haultfoeuille et al., 2014; Huse and Lucinda, 2014) alone or imposed on top of a fuel economy label program (D'Haultfoeuille et al., 2013). Fourth, fuel- or energy-efficiency labels (or similar certification systems) are currently applied in the European Union and other countries for many durables, and plans to extend them to many others (e.g., used cars, certain types of machinery) are currently under consideration. It is therefore important to understand the implications of introducing these schemes.

That the label might have an effect on price rests on the assumption that auto importers believe that consumers value the fuel economy of a car, or the additional information conveyed by the label, or derive utility from the label per se. Earlier research has sought to estimate the fuel economy premium using hedonic pricing methods, but hedonics empirical work 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; Witt, 1997; Murray and Sarantis, 1999; Matas and Raymond, 2009).

Espey and Nair (2005) and Busse et al (2013) find evidence of a dollar-for-dollar tradeoff between the price of a car and discounted future fuel costs. Allcott and Wozny (2014) find that only about 70% of future fuel costs is captured into the price of a car, and Sallee et al. (2011) conclude that the discounting is slightly less pronounced than that. Qualitative research 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). Consumer failure to consider future fuel costs is seen as an argument in favor of regulatory approaches over market-

3. The voluntary agreement did not attain the goals, and so in 2007 the European Union established regulations imposing corporate average CO_2 emissions limits on automakers, which were phased in starting in January 2012. Switzerland has adopted these regulations, which were phased in starting in July 2012.

based instruments, such as fuel taxes (Williams and West, 2005; Bento et al., 2009; Anderson et al., 2011).

On the other hand, 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 savings on the energy bills (Newell and Siikamaki, 2013), and 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). This has been interpreted as willingness to contribute to the public good.

One important feature of the Swiss label system is that label assignment is strictly based on a numeric variable and on the range that it falls into for any given car. A tiny change in this numeric variable may grant assignment to a better or worse label category. In other words, label assignment is based on "notches" (Sallee and Slemrod, 2011), which may encourage product manipulation to take advantage of whatever benefit may be associated with falling in one rather than the next notch. This product manipulation is sometimes observed in the form of "bunching" at the boundary between categories, which allows manufacturers to meet standards and avoid penalties, with little actual effect on overall fuel or energy efficiency (Sallee and Slemrod, 2011; Houde, 2014b; Ito and Sallee, 2014).

We find little or no evidence of product manipulation in the Swiss new car market, consistent with the fact that Swiss auto importers have no influence over the producers' design and manufacturing process, but we do find evidence that auto importers were seeking to charge higher prices for cars meeting the "A" label requirements in comparison to otherwise identical cars that barely missed the threshold for the "A" label. Based on our regression discontinuity design (RDD), 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%.

The remainder of this paper is organized as follows. Section 2 provides background information about the Swiss label scheme, and section 3 discusses possible auto importer responses to the label system. Section 4 presents the econometric models and estimation approaches, section 5 the data and section 6 our RDD data checks. 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. The A-G label classes and their graphical depiction are similar to the label system used throughout Europe for homes and electrical appliances.[4] 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).

4. See https://en.comparis.ch/carfinder/info/glossar/energieetikette.aspx (last accessed 18 October 2015).

In addition to car make and model, fuel type, transmission, and curb weight, the label displays fuel consumption, 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 settings, the Swiss labels do not report fuel costs per unit of distance or for the average driver over a year.

The Swiss energy label is based on combining absolute and relative fuel consumption, which allows even larger and heavier cars to attain the best categories.[5] The first step towards this classification is to compute each vehicle's rating number (RN). In 2003, when the system was established, SFOE calculated RN by applying the formula:

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

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 kilograms. It is easy to show that RN is the harmonic mean of the absolute fuel economy (i.e., the distance covered using one kg of fuel) and the *relative* fuel economy (the distance covered using one kg of fuel per unit of weight of the car).

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

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

which 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 better fuel efficiency.

The SFOE creates the cutoffs for assigning a car to each of the seven efficiency classes (A-G) by gathering the RN scores from all new cars approved for sale in Switzerland in the two years prior to the reference date (November 30), and selecting the largest RN in the bottom seventh of this distribution as the boundary for category A. The RN cutoffs are thus revised every two years. 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 cutoffs for placement in each class are summarized in Table 1.

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

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

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.[6]

5. 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). By contrast, France and Denmark's systems rely on absolute fuel consumption.

6. The bandwidth used by the Swiss Federal Office of Energy for creating the label classes is not the bandwidth we use in our RDD to identify the effect of the label above and beyond that of the fuel economy and other car characteristics (see section 4 of this paper).

Table 1: Thresholds for Placement in the Different Label Classes During the Study Period

Year	Threshold for A label	Threshold for B label	Threshold for C label	Threshold for D label	Threshold for E label	Threshold for F label
2003	20.30	22.10	23.90	25.70	27.50	29.30
2004	18.90	20.74	22.58	24.42	26.26	28.10
2005	18.90	20.74	22.58	24.42	26.26	28.10
2006	26.54	29.45	32.36	35.27	38.18	41.09
2007	26.54	29.45	32.36	35.27	38.18	41.09
2008	26.22	28.95	31.68	34.41	37.14	39.87
2009	26.22	28.95	31.68	34.41	37.14	39.87
2010	24.72	27.20	29.68	32.16	34.64	37.13
2011	24.72	27.20	29.68	32.16	34.64	37.13

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. The absolute measure is thus weighted more heavily in the new system. The data used in this paper stop at 2011 and are not affected by these changes.[7]

3. AUTO IMPORTERS RESPONSES TO NOTCHES AND LABELS

Sallee and Slemrod (2011) describe notches, namely settings where the applicable regulations or tax rates change in a discontinuous fashion with respect to the values of the variable subject to the regulations or tax. Notches encourage small changes in behaviors or product adjustments, and yet result in large changes in outcomes. The US gas guzzler tax, for example, is paid for by automakers or auto importers, and the exact amount of the tax depends on the fuel economy interval that each particular car falls into. Sallee and Slemrod document the automakers' tendency to adjust the fuel economy of cars so that they fall into the tax-favorable side of the cutoff between adjacent fuel economy categories. This results in "bunching," i.e., a large number of models at or barely to the right of the miles-per-gallon cutoff between each category and the next, while frequencies are lower to the left of the cutoffs.

Sallee and Slemrod (2011) further argue that the fuel economy labels that must be affixed to new cars for sale in the US provide a similar incentive to automakers, as the fuel economy figures are rounded to the nearest integer, and report evidence of such behaviors, especially among US automakers. Ito and Sallee (2014) study attribute-based regulation when notches are present and based on attribute (weight) other than the one being regulated (fuel economy). In Japan, this has created an incentive for the automakers to increase the weight of a vehicle so that the applicable fuel economy standard is less stringent. Houde (2014b) finds evidence of bunching around the federal energy efficiency standards for domestic appliances sold in the US.

As explained in section 2, in the Swiss car system label assignment depends on the interval where the car's RN score falls, and as such it is based on notches. In this paper, we check for the presence of bunching (see section 4), but our main concern is not bunching per se, but rather the possibility that auto importers might take advantage of the notches to charge highr prices for certain vehicles.

7. We restrict the analysis to 2011 and earlier years to avoid potential responses in anticipation to the corporate average CO_2 emissions regulations, which were phased in Switzerland in July 2012.

If the auto importers believe that car buyers are willing to pay a premium for a car that attains a better label category (e.g., an “A” car versus an otherwise similar car that receives a “B” label), then they will attempt to charge such premium.[8] Why would car buyers be willing to pay a premium for a car that has earned a better label? It is possible that some may simply derive utility from knowing that that their vehicle has attained a better label, even though they are perfectly aware of the fuel economy of the vehicle per se. Kotchen and Moore (2009) and Jacobsen et al. (2012), for example, document that consumers are willing to pay higher tariffs for an otherwise identical good (electricity) if it has been produced using environmentally friendly technologies. Houde (2014b) likewise reports that in the US domestic appliance market manufacturers do charge a premium for appliances with an energy efficiency certification, and this premium is greater than the energy cost savings made possible by the appliance.

For consumers who are “rationally inattentive” (Sallee, 2014) the label may help dispel uncertainty about the fuel economy and/or the carbon emissions of the vehicle (bearing in mind that no information about the annual cost of driving is displayed in the Swiss labels), or replace the conventional fuel economy information. Rational inattention is consistent with Houde‘s (2014a) three types of consumers. To one type, the energy efficiency certification (“Energy Star” status) does not convey additional information that was not already included in the energy efficiency of the appliance. To another type, the certification supplements the mere energy efficiency figures, while the third type ignores both because energy efficiency is not important to them. The model implies that one group of consumer would be willing to pay extra for an appliance that attains the “Energy Star.”

The presence of different consumer types is sufficient to predict that the Swiss auto importers will attempt to charge a premium for cars that receive better fuel economy labels (see Houde, 2014b). These considerations, however, do not shed light as to whether the auto importers seek to charge a premium only for “A” cars, or also for B cars over C cars, C cars over D cars, etc. We turn to empirical analysis to look for evidence of such behavioral responses.

4. APPROACH

4.1. Preliminary Checks: The Hedonic Pricing Approach

In principle, the most straightforward approach to examining whether a vehicle’s fuel economy is capitalized into the vehicle’s price, and whether the labels have an additional effect, is to estimate a hedonic pricing regression (Rosen, 1974; Bockstael and McConnell, 2007). In such hedonic pricing regressions, price (or its logarithmic transformation) is regressed on car characteristics, fuel economy, and the label dummies. Significant coefficients on the label dummies would be interpreted as evidence that attaining a particular fuel economy category matters, above and beyond the effect of the fuel economy per se.

In practice, hedonic pricing regressions are rife with econometric problems, including collinearity between the fuel economy and other vehicle attributes, and, even more important, the possibility that that fuel economy might capture omitted car attributes that are correlated with it,

8. Setting higher prices for vehicles with better fuel economy labels does carry the risk that demand for such vehicles might fall. Presumably the auto importers will take that into account and seek to set the prices so as to maximize profits It is also possible that auto importers seek to raise the price of vehicles with better fuel economy labels to discourage their sales in favor of other vehicles that ensure higher profits.

which would result in biased estimates of the value of the fuel economy (Atkinson and Halvorsen, 1984; Knittel, 2011). Even if one were able to address these difficulties, one would expect the label dummies to be highly correlated with the (continuous) fuel economy measure included in the model, which may make the estimates unstable and difficult to interpret.

We do run hedonic pricing regressions using our data from Switzerland to get an initial sense of whether the market rewards a vehicle's fuel economy (or, to be more precise, if the car importers expect it to), and resort to a regression discontinuity design and matching estimation to circumvent some of the abovementioned difficulties.

We have the full list of passenger vehicles approved for sale in Switzerland from 2000 to 2011, complete with make, model, trim and variant, various characteristics (including fuel type and fuel economy information), and manufacturer-suggested retail prices (MSRPs).[9] For 2005–2011, we also have the sales of each new make-model-trim-variant in each year. Attention in this paper is restricted to gasoline and diesel cars, which account for over 99% of all cars.

The dependent variable in our hedonic pricing regression is log price.[10] We have a number of possible measures of fuel economy. The first is the fuel consumption in liters per 100 km,[11] converted into gasoline-equivalents (FUELEQUI).[12] The lower FUELEQUI, the better the fuel economy of the car. The second is FUELEQUI divided by the weight of the vehicle, which we term the relative fuel consumption rate. The third is the RN score, which is a weighted average of the former two (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 1), to produce fuel cost per 100 km (expressed in 2011 Swiss Francs [CHF]). These four measures are strongly correlated with one another, so that, in practice, only one of them can be included in the right-hand side of a hedonic regression, and with the fuel economy labels.

4.2. Assessing the Effect of the Label: Regression Discontinuity

We take advantage of the SFOE's rule to identify the effect of the label on price using a regression discontinuity design. Regression discontinuity designs (RDDs) can be applied to estimate

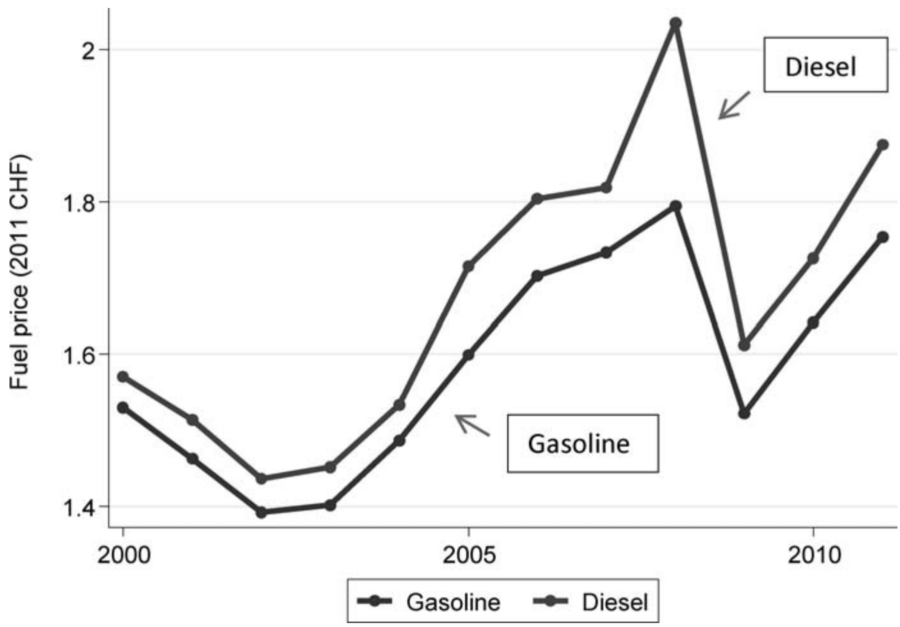
9. We define as passenger cars light-duty vehicles with no more than 9 passenger seats, maximum weight 3500 Kg. and not meant for transporting commercial goods. In general, car models are differentiated by the "trim" level, and additional differences exist across variants of the trims, but there is considerable 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.

10. We use log price consistently in our hedonic regressions as well as in our RDD and matching approaches. We use the log transformation of price, instead of price, for the usual reasons, e,g., it reduces the effect of gross outliers and makes the distribution unimodal and symmetric. All of our regressions are log linear models, and all of our results are robust to replacing log price with price (results available from the authors). We emphasize that in this paper we estimate "reduced form" models—not "structural" model to test if consumers discount dollar-for-dollar future fuel cost into the current price of the vehicle. Such "structural" models would indeed imply regressing (untransformed) price on $\left[\sum_i \delta^t M_t \cdot (liters/100km) \cdot pf_t\right]$ where t denotes the time period, M is kilometer driven (in hundreds) in year t, pf is the price of fuel in year t, and δ^t is the discount factor in period t. One would then assess the magnitude of the coefficient on the terms in the brackets to see if it is negative one or less. This is the approach in Espey and Nair (2005), Allcott and Wozny (2014), and Sallee et al. (2011).

11. This is based on combined city and highway fuel consumption.

12. 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.

Figure 1: Fuel Prices in Switzerland, 2000–2011



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 (see equations (1) and (2)), and the cutoffs for class A during our study period are reported in Table 1. 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 *RN* is the rating score, *T* is the A-group cutoff value, within a narrow range around zero. We fit polynomials up to order three with interactions between the treatment (the A label) and the polynomial terms to allow for the slope of the local regression function to be different across the cutoff:

$$\ln P_i = a + b\cdot A_i + c\cdot(RN_i - T) + d\cdot A_i\cdot(RN_i - T) + f\cdot(RN_i - T)^2 + g\cdot A_i\cdot(RN_i - T)^2 + k\cdot(RN_i - T)^3 + m\cdot A_i\cdot(RN_i - T)^3 + \eta_i \quad (4)$$

The treatment effect is thus b, the coefficient on A_i, a dummy variable indicating whether vehicle i attains fuel efficiency label A.

If f, g, k and m are all equal to zero, equation (4) is simplified to a local linear regression with a rectangular kernel (Lee and Lemieux, 2010). We fit this and local linear regressions with a triangular kernel (Hahn et al., 2001), where the ATT is computed as $\hat{a}^- - \hat{a}^+$, with

$$(\hat{a}^{-},\hat{b}^{-}) = \operatorname{argmin} \sum_{i \in B^{-}} (\ln P_i - a - b \cdot (RN_i - T))^2 K\left(\frac{RN_i - T}{h}\right) \tag{5}$$

$$(\hat{a}^{+},\hat{b}^{+}) = \operatorname{argmin} \sum_{i \in B^{+}} (\ln P_i - a - b \cdot (RN_i - T))^2 K\left(\frac{RN_i - T}{h}\right) \tag{6}$$

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.

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 variable (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 note that if condition i) is verified, then there is no bunching at the cutoff between label A and B. We empirically check that there is no bunching at the cutoffs for the different labels, even if we do not expect any to exist. This is for five reasons. First, in the Swiss label system there is no direct tax or regulation avoidance associated with attaining a particular label. Second, unlike the US car or domestic appliance market, there is no local manufacturing and auto importers cannot make product adjustments themselves. Third, Switzerland is a small market and (foreign) automakers have no incentive to make product adjustments for the Swiss market alone. Fourth, the cutoffs for the various labels are changed every two years so even if product adjustments were possible, they would be rendered useless quickly. Fifth, an individual importer has no ability to influence the overall distribution of fuel economy and hence the cutoffs established by the SFOE.

4.3. 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, which rely on combining a car's absolute and relative fuel economy, allow vehicles with very different *absolute* 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.[13] For each A-class vehicle, we will thus look for a match—a vehicle with the same continuous measure of absolute fuel economy, and similar in other aspects, but that has received a B label—and compute the price differential between them.[14] Once these price differentials are averaged over all possible pairs of

13. 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.

14. Our matching algorithm minimizes the Mahalanobis distance. We use the absolute fuel economy (along with other car attributes) as a matching variable for two reasons. First, this is the measure listed in manufacturers' spec sheets and on the labels themselves, and thus the one that should matter to consumers, who are not privy to SFOE's ratings and cutoffs. Second, we cannot use the SFOE's rating scores because they predict perfectly whether the vehicle receives the A label. This would violate the overlap assumption required for the matching approach, namely that the probability of treatment is

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

$$\gamma_A^{matching} = \sum_x \Delta_x P(X_i = x | A_i = 1) \tag{7}$$

where Δ_x denotes the price differentials for matched observations and $P(X_i = x | A_i = 1)$ 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 (7) would be consistent and asymptotically normally distributed. With continuous variables, however, Abadie and Imbens (2011) show that (7) 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 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 (see Abadie and Imbens, 2006, p. 239). 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.

Finally, within a given matching algorithm it is possible to impose restrictions to ensure exact matching with respect to binary or categorical variables, requiring, for example, that diesel cars be matched solely with diesel cars, and/or sedans be matched solely with sedans. We experiment with imposing and relaxing some of these restrictions to see if they affect the results.

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. For 2005 and later years, we also have new car registrations from the Motorfahrzeuginformationsystem (MOFIS) dataset compiled by the Federal Roads Office. New car registrations track almost perfectly new car sales. We use the make-model sales figures as weights in our regressions.

between zero and one for both control and treated vehicles (Heckman et al., 1998). This is also the reason why propensity score matching is not possible here, as the key attributes of a vehicle (fuel economy and weight) predict near-perfectly if a vehicle receives the A label.

Table 2: Descriptive Statistics of the Sample (Only Diesel and Gasoline cars; No Russian, Indian or Romanian Cars; No Exclusion = 1[a]). N = 45,730

Variable	Description	Mean	Std. Dev.	Min	Max
preis2011	price in 2011 CHF	43422	18723	10278	270000
lpreis2011	lnpreis 2011	10.60	0.405	9.2375	12.5062
A	A label	0.22	0.413	0	1
B	B label	0.17	0.378	0	1
C	C label	0.20	0.398	0	1
D	D label	0.17	0.377	0	1
E	E label	0.13	0.332	0	1
F	F label	0.08	0.268	0	1
fuelequi	fuel per 100 km in gasoline equivalent	7.70	1.703	3.36	12.10
fuel_weight	fuelequi/1000 kg	5.14	0.926	2.71	13.00
costper100km	fuel cost per 100 km (2011 CHF)	12.14	2.852	4.35	21.98
Weight	weight (tons)	1.51	0.278	0.67	2.81
hp_weight	horsepower per 100 kg	9.54	2.617	4.38	41.66
engine_size	engine size in liters	2.00	0.577	0.60	5.67
Diesel	Diesel dummy	0.39	0.487	0	1
automatic	automatic transmission	0.36	0.480	0	1
AWD	all-wheel drive	0.16	0.365	0	1
benzineturbo	turbocharged and gasoline powered	0.03	0.169	0	1
Cabriolet	Convertible	0.03	0.179	0	1
SUV		0.08	0.274	0	1
Station_Wagon		0.23	0.421	0	1
Coupé		0.02	0.146	0	1
Van	Minivan	0.12	0.327	0	1
microcar		0.03	0.166	0	1
subcompact		0.11	0.309	0	1
compact		0.23	0.424	0	1
Midsize		0.27	0.446	0	1
Fullsize		0.12	0.328	0	1
ttueren2	2-door	0.14	0.344	0	1
ttueren3	3-door	0.19	0.392	0	1
ttueren4	4-door	0.63	0.483	0	1

[a] Vehicles with fuelequi > = 12.10 (the 95[th] percentile of the distribution) are excluded.

Attention is restricted to gasoline and diesel cars. Other fuels account for less than half of one percent of the observations. We have 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.

Our preliminary hedonic pricing regressions are based on a sample that further excludes the top 5% of the distribution of 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.

Car imports into Switzerland are clearly dominated by the German automakers (see Alberini et al., 2014, page 23), with French cars a distant second. Table A.1 in the online Appendix 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 2. The mean price is CHF 43,422 and the median price is about CHF

Table 3: Car Characteristics over the Study Period: Averages by Year. Only Diesel or Gasoline, No Russian, Indian or Romanian Cars

Year	Weight (1000 kg)	Fuelequi (liters/100 km)	fuel_weight (liters/100 km per 1000 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

40,000. The second panel of Table 2 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 2 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 3, in this sample the average car weight has slightly increased and then decreased over time, while fuel economy improved steadily.[15] 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 4 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 when the sample includes mid- and full-size cars. Nevertheless, the share of A-label cars is higher among the smaller cars.

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

Table 4: 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.[a]

Measure	Fuelequi (liters/ 100km)	fuel_weight (liters/100km per 1000 kg)	costper100km (2011 CHF)	Weight (thou. Kg)	A[b] (share)	Diesel (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
Gasoline	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

[a] Vehicles with fuelequi > = 12.10 (the 95th percentile of the distribution) are excluded.
[b] 2003 and later.

The distributions of FUELEQUI for diesel and gasoline vehicles are positively skewed, and the former lies to the left of the latter. Figure 2 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 cost-per100km 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.

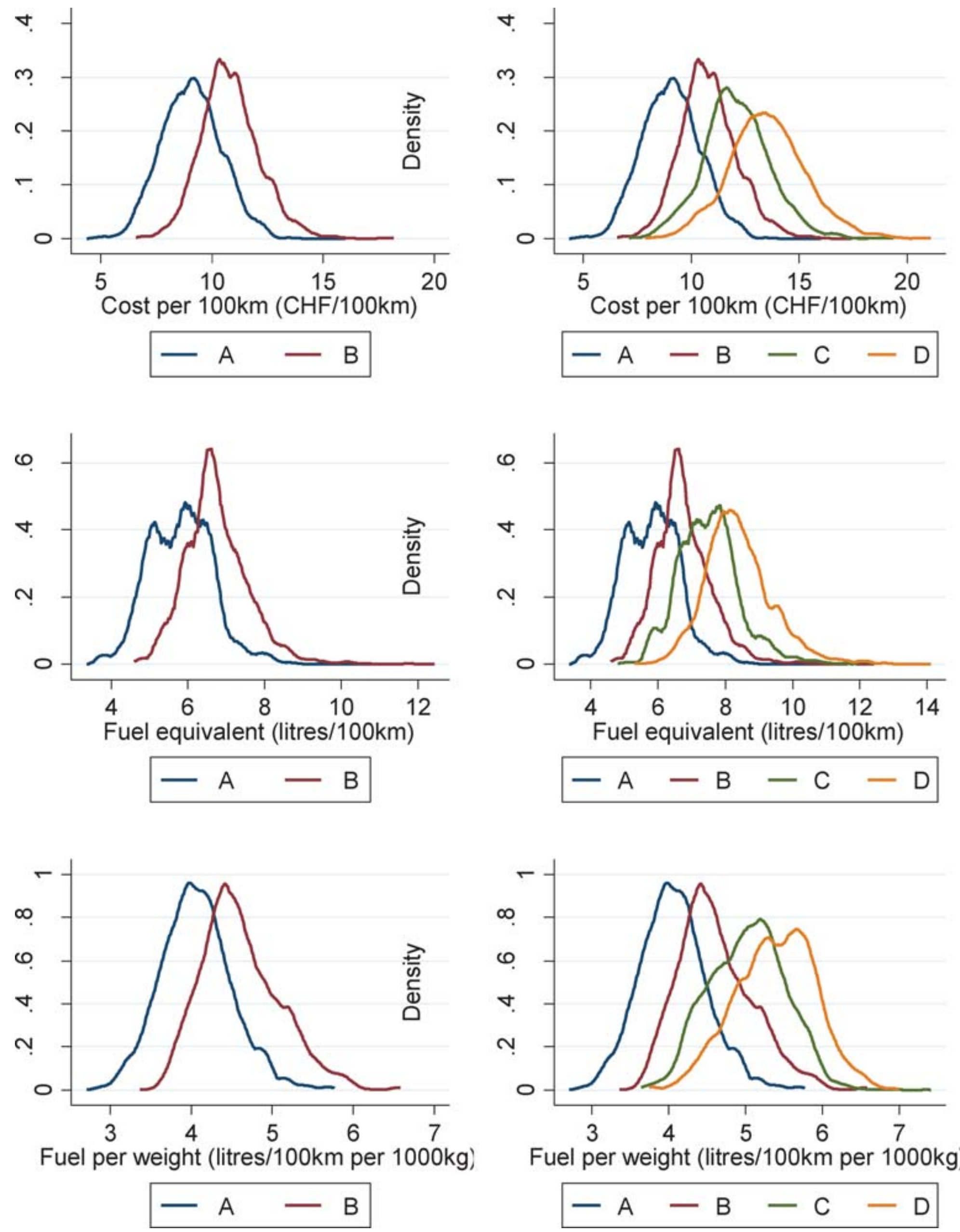
6. BASIC CHECKS FOR THE REGRESSION DISCONTINUITY DESIGN

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, which is small enough to contain only A and B vehicles (see Table 1).

Our first order of business is to make sure that there are no discontinuities in the density of the driver variable, RN (the vehicle's score based on SFOE's formula), across the cutoff for the A label. 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 A.1 in the online Appendix 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, 2008) likewise suggests that RN is discontinuous at the cutoff in 2003 (see Figure 3a), 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 3b). For this reason, we fit equations (4)–(6) to 2004 and later years.

Figure 2: Distribution of Various Measures of Fuel Consumption by Label Class



Next, we check that the covariates are balanced across the cutoff within the selected bandwidth. Table 5 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).

Figure 3a: Density of (RN-T), where RN = Rating Score and T = Cutoff for A Label, 2003

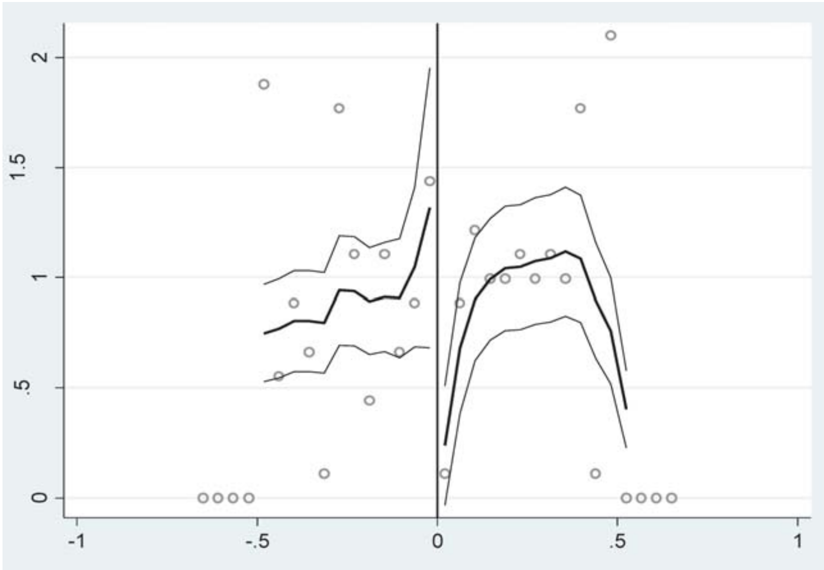
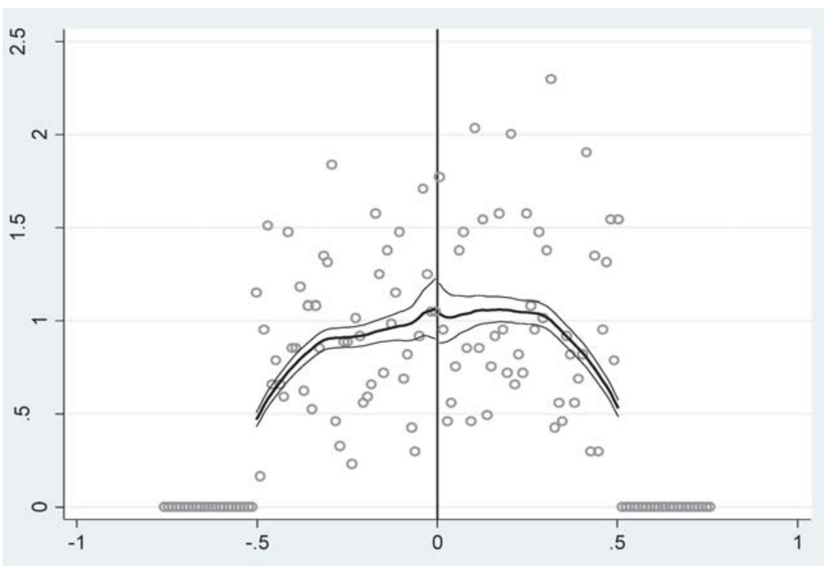


Figure 3b: Density of (RN-T), where RN = Rating Score and T = Cutoff for A Label, 2004–2011



Note: the density is estimated separately from the left and the right of zero by the McCrary test (2008). The thicker solid line is the fitted density. The thinner solid lines trace out the 95% confidence interval around the fitted density.

This means that we must control for these variables when we run our local regression discontinuity regressions. In other words, they must be included in the right-hand side of RDD regressions (5)–(7). The covariates appear to be smooth across the cutoff.

Table 5: 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

Figure 4: Evidence of Regression Discontinuity: Mean ln Price by (RN-T) Bandwidth, where RN = SFOE's Rating Score and T = Cutoff for the A Label

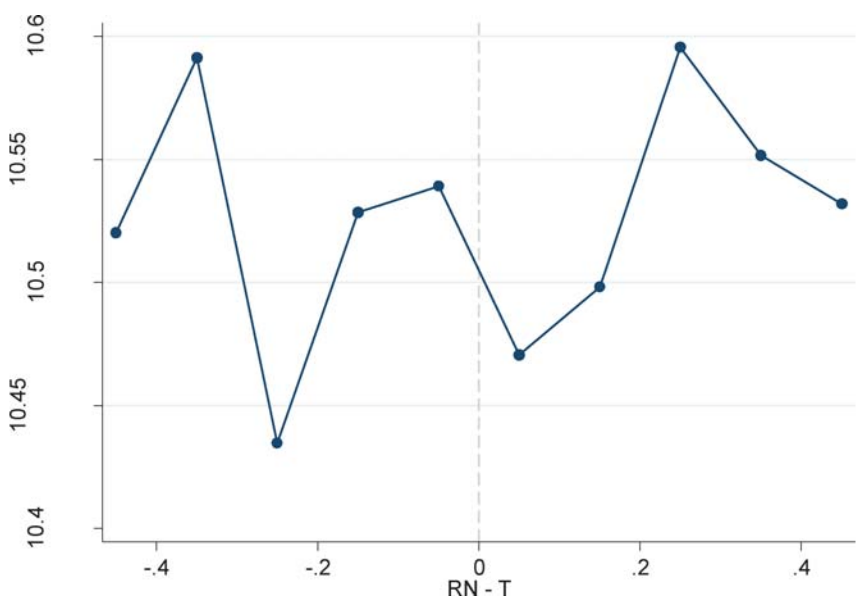


Figure 4 displays the average log price by (RN–T) bins, where T denotes the cutoff for the A label, suggesting evidence of a discontinuity in prices at the threshold for class A and of a non-linear relationship between (RN-T) and log price away from the cutoff. The mean log price in the bin immediately to the left of the cutoff is statistically different at the 5% or better from that in

Table 6: Descriptive Statistics of Vehicles by Fuel Economy Label. All Cars (except for Russian, Romanian and Indian-made Cars)

Label	Mean Price (2011 CHF)	Diesel share	Mean Engine size (liter)	Mean Power (kW)	Sales 2003–2011
A	36,798	0.875	1.734	86.30	467,919
B	39,941	0.552	1.830	97.44	547,369
C	42,280	0.322	1.904	103.9	591,459
D	45,917	0.196	2.051	114.5	433,853
E	52,282	0.0665	2.304	133.6	273,854
F	65,090	0.0369	2.821	161.6	114,644
G	123,467	0.0117	3.947	241.0	100,326
Total	50,982	0.385	2.163	119.9	2,529,424

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.

When we perform similar checks across the cutoffs for the other labels, the histograms, McCrary tests, and covariate balance checks for B v. C cars, and C v. D are qualitatively very similar to the ones above for A v. B cars. The test for the continuity of the driver variable fails for D v. E, E v. F, and F v. G, although in these cases the “excess” density is to the *right* of the cutoff, not to the left as one would expect if auto importers were reacting strategically to the labels (results available from the authors). Perusal of Table 6 suggests that engine size, horsepower, and price increase dramatically as we move from the A to G categories, whereas the share of diesel vehicles decreases regularly, to the point that it is practically zero among G-rated vehicles. For E and higher labeled-vehicles, it seems likely that other attributes are the main determinants of the car’s price, and that the fuel economy becomes irrelevant. Based on these considerations and the discontinuity of the driver variable for D v E, E v. F, and F v. G cars, we limit our RDD analyses to A v. B, B v. C and C v. D vehicles.

7. RESULTS

7.1. The Fuel Economy Premium

We begin with discussing our hedonic pricing regressions results. We regress log price (expressed in constant 2011 CHF) on car weight, engine size, horsepower per unit of weight, and dummies for number of doors, body type, transmissions, fuel type (gasoline or diesel), all-wheel drive, and gasoline turbocharged engine. We further include one continuous measure of fuel economy (see below), year fixed effects, and make-model fixed effects, which means that the effect of fuel economy (or other any regressor) on price is identified by the variation in the “trims” or “variants” within a make-model.[16] Polynomials in weight and horsepower per unit of weight are

16. 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. In and after 2003, 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. 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 mitigate the possible endogeneity

Table 7: Hedonic Regression Results: Summary of Coefficients on Fuel Consumption Rate and Fuel Type from Alternate Specifications*

	2000–02		2000 +		2003 +		2005 +		2005 + sales weighted	
	coeff	t stat	coeff	t stat	Coeff	t stat	coeff	t stat	coeff	t stat
microcar, sub-compact, compact[a]										
Fuelequi	0.001	0.3	−0.035	−37.87	−0.042	−41.63	−0.043	−38.37	−0.037	−31.71
Diesel	0.131	14.13	0.109	41.8	0.106	37.4	0.109	35.41	0.010	29.05
Fuelequi	0.034	9.91	0.011	7.66	0.006	3.95	0.007	4.20	0.003	1.45
Diesel	0.068	9.84	0.093	57.19	0.097	57.36	0.098	53.58	0.096	43.87
Nobs	2,125	15,850	13,725	11,227	11,031					
up to midsize[b]										
Fuelequi	−0.006	−3.39	−0.028	−43.35	−0.032	−46.23	−0.032	−41.82	−0.028	−35.29
Diesel	0.140	21.8	0.11	62.06	0.107	56.09	0.108	52.75	0.100	47.21
Fuelequi	0.032	13.4	0.015	16.72	0.012	12.09	0.013	11.95	0.009	8.18
Diesel	0.077	17.17	0.088	75.19	0.089	73.37	0.089	67.86	0.088	59.49
Nobs	3,900	28,175	24,275	19,629	19,396					
up to fullsize[c]										
Fuelequi	−0.003	−2.39	−0.023	−46.83	−0.027	−45.09	−0.027	−40.26	−0.025	−35.31
Diesel	0.137	26.8	0.113	74.17	0.109	66.03	0.110	61.73	0.103	55.95
Fuelequi	0.034	17.57	0.018	24.42	0.015	17.93	0.016	17.10	0.012	13.07
Diesel	0.072	19.18	0.085	82.57	0.086	79.40	0.087	73.03	0.086	65.89
Nobs	4,879	34,478	29,599	23,849	23,577					
All[d]										
Fuelequi	−0.006	−5.12	−0.024	−48.36	−0.028	−52.52	−0.029	−47.68	−0.024	−39.48
Diesel	0.141	31.73	0.112	82.53	0.107	73.05	0.107	67.88	0.104	65.13
Fuelequi	0.032	19.57	0.016	24.66	0.013	16.85	0.013	15.64	0.013	15.94
Diesel	0.077	24.84	0.088	93.68	0.089	90.17	0.089	83.17	0.086	75.6
Nobs	6,687		45,730		39,043		31,782		31,027	

* The dependent variable is log price, and the regression includes make-model fixed effects, year fixed effects, control variables, plus one fuel economy measure. Each row in the table displays only the coefficient(s) and t statistic(s) for the main fuel economy variable(s) in each regression.
Note: fuelequi is the gasoline-equivalent consumption per 100 km.
[a] fuelequi ≥ 3.9 &fuelequi ≤ 8.624.
[b] fuelequi ≥ 3.9 &fuelequi ≤ 10.192.
[c] fuelequi ≥ 3.9 &fuelequi ≤ 11.2.
[d] no fuelequi range restrictions.

included in hopes of soaking up any other vehicle characteristics that influence price but are not documented in our dataset.[17]

Table 7 displays selected regression coefficients based on using FUELEQUI as the continuous measure of fuel economy. The results displayed in the first row of each panel of Table 7

between price and fuel economy, to the extent that this endogeneity is driven by make-model-specific unobservables that are approximately constant over time.

17. 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.

Table 8: Regression Discontinuity Design: Results from Local Linear Regressions

	Triangular Kernel regression			Rectangular Kernel regression		
	(1) A v. B	(2) B v. C	(3) C v. D	(4) A v. B	(5) B v. C	(6) C v. D
ATT	0.0786**	−0.0441	0.0110	0.0864**	−0.0420	0.00166
	(3.12)	(−1.81)	(0.28)	(3.26)	(−1.63)	(0.04)
N	2757	3113	2828	2757	3113	2828
Optimal bandwidth	0.2650	0.2327	0.1303	0.2082	0.1828	0.1024

Notes: t statistics in parentheses. Covariates used: Diesel microcar subcompact compact Van SUV automatic AWD doors3 doors4 door5.
* $p<0.05$; ** $p<0.01$; *** $p<0.001$

suggest that there *is* a fuel economy premium in all market segments (although the effect is strongest in the small car segment). Using the coefficients from the regressions with data from 2003 and later, for example, 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).

The results are robust to using sales-weighted least squares, but not to adding a dummy denoting that the car runs on diesel. While the coefficient on the diesel dummy is approximately 0.11, that on FUELEQUI becomes 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.[18]

One difficulty with interpreting these findings is that, due to the extremely high collinearity between the diesel dummy and the continuous fuel economy measure(s), we cannot say unambiguously whether, all else the same, consumers are asked to pay higher prices for better fuel economy or for diesel engines. (Diesel engines are more expensive to produce, but last for more miles and are often thought as requiring less maintenance than gasoline engines.) Adding the label dummies only exacerbates the collinearity problem.[19]

If we enter the label dummies in the hedonic regression but exclude any continuous measure of fuel consumption as well as 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. These results (not reported) are based on 2003 and the subsequent years.

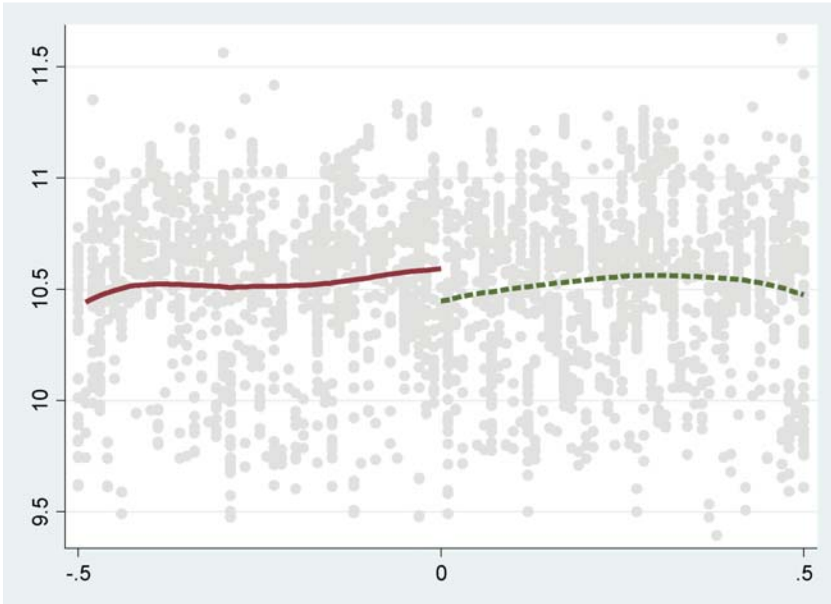
7.2. Regression Discontinuity

The estimation results from the regression discontinuity approach indicate that qualifying for the A label has a positive and significant effect on price (Table 8). We control for covariates found to be unbalanced across the cutoff (diesel, car size and body type, automatic transmissions,

18. In Table A.2 in the online Appendix, we 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.

19. Adding the label dummies when the diesel dummy and a continuous fuel economy measure are present changes the signs of the coefficients on the latter variables, and results in implausible and negative effects for all labels better than G.

Figure 5: Regression Discontinuity Estimation: Local Linear Regression with Triangular Kernel (see equations (4)–(6)), Bandwidth ± 0.5 from the Cutoff



Note: All years later than 2003. The model controls for Diesel, car size, body type, number of doors, automatic transmission and AWD. The solid and dashed lines show the log price predicted from the RDD regression model.

all-wheel-drive and number-of-doors dummies). The local linear regression with triangular kernel estimates the ATT to be 0.0786 (t statistic 3.12), for an 8.17% increase in price, at the optimal bandwidth, which is about 0.26.[20] The discontinuity in log price at the cutoff is apparent in Figure 5. The local linear regression with rectangular kernel estimates the ATT to be 0.0864 (t statistic 3.26) at the optimal bandwidth (0.2082). This implies a 9.02% increase in price.

We check that the local linear regression is adequate in Table A.3 in the online appendix, which reports results for linear, quadratic and cubic polynomials for various bandwidths, and tests whether the higher-order terms in (RN-T) can be safely omitted or should be kept in the regression. Table A.3 shows that the ATT estimated from the local linear regressions reported in Table 8 agree 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 similar to the optimal ones from the local linear regressions above, the estimated ATT is 0.0733 (t statistic 2.25) and the associated effect on price 7.6%.

Additional sensitivity checks with respect to changing the bandwidth and the order of the polynomial in Table A.3 in the online Appendix 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

20. 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, namely that which minimizes the mean square error of the estimate of the ATT.

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.[21]

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.[22]

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. 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 2004 or later, and then with the data from 2004 to 2009.[23] 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.

We also used the regression discontinuity approach to see if qualifying for a B label brings a price premium over a comparable C car with a fuel consumption rate barely above the B label threshold. Visual inspection of the data suggests once again an initial bandwidth of ± 0.5 from the cutoff for the B label. The ATT based on local linear regressions (with triangular or rectangular kernel) suggest a 4% *decline* in price when attaining the B label compared to an otherwise similar C car, but the effect is insignificant at the conventional levels (see Table 8, column (5)). Quadratic and cubic polynomials suggest unstable and generally insignificant ATT estimates ranging from a 4% decline to a 4% increase in price.

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 1% or less, and statistically insignificant at the conventional levels. For example, the local linear regression with triangular kernel produces an estimated ATT of 0.010, with a t statistic of 0.28 (see Table 8, column (3)).

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

22. 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.

23. 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 modest.

The findings of a significant A-label premium are robust to repeating the RDD estimation separately for gasoline and diesel vehicles. With gasoline cars only, the label premiums are slightly stronger and statistically significant (and of the order of 3–4%) even in B v. C and C v. D groups.

7.3. Matching

We limit our matching estimation to the broad group of A and B cars, since the earlier analyses suggest that the only A-label premium is robust with respect to a variety of checks, specification and subsamples of the original data. The results of various runs of our matching estimation procedure are displayed in Table 9. 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.

The results in Table 9 are based on the bias-adjusted procedure, 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.[24] 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.[25]

8. CONCLUSIONS

We have used price and car characteristics data from the Swiss car market in 2000 – 2011 to see whether the fuel economy of a vehicle is capitalized into its price, and, even more important, if fuel economy/CO_2 emissions labels have an additional effect on price, above and beyond that of the fuel economy. We have exploited a dataset with a unique level of detail and multiple measures of a vehicle's fuel economy.

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 using hedonic regressions. 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. We take advantage of the clean mechanism used by the Swiss federal government to assign each vehicle to the appropriate fuel economy label, which allows us to apply sharp RDD estimation. This mechanism, the driver variable it uses, and the availability of other measures of fuel economy allows us to apply matching methods in hopes of improving the external validity of our findings.

We find convincing evidence of a 6–11% increase in price when the threshold is crossed. The jump in price is much smaller, or absent altogether, when the threshold for less desirable labels (B, C, etc.) is met. The results are robust to a variety of robustness checks, and appear to be slightly stronger within gasoline-powered cars. Our matching estimators exploit the fact that in our dataset

24. 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.

25. 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 should 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.

Table 9: 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

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

there are cars with the same absolute fuel economy but different SFOE-assigned labels. This approach indicates that there is a 5% price premium associated with attaining the best efficiency class.

These results suggest that auto importers believe that the public is willing to pay more for a car when it receives the A certification. The fact that the fuel-economy premium is smaller or absent altogether for labels B and C further suggests that auto importers expect consumers to be heterogeneous, and expect those consumers who place the highest value on the fuel economy to purchase the cars with the best fuel economy.

That consumers appear to be willing to pay more for an otherwise identical good when it receives an “environmentally friendly” or “energy efficient” certification has been observed in other contexts (Kotchen, 2009; Jacobsen et al., 2012; Houde, 2014). In some of these contexts the certification is voluntary for the producers, and that consumers are willing to pay for a product with such a certification has been interpreted as suggesting that it serves as a substitute for finer but more complex information about the energy efficiency of the product.

Our case is different, because the fuel economy label is mandatory for new cars. Label assignment is based on notches, which have been found in related contexts to create strategic incentives for producers to adjust product attributes (Sallee and Slemrod, 2011; Houde, 2014; Ito and Sallee, 2014). While the auto importers had relatively little or no room for strategic responses in terms of the types of cars to be 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.

Our data and calculations indicate that for vehicles that received rating scores very close to the requirement for the A label, the "markup" is up to 11%, even though fuel economy and CO_2 emissions are practically unchanged across the cutoff. In 2011, when 25.9% of all new cars sold were A-label cars, the total "markup" was of the order of CHF 152 million.[26] We conclude that label systems based on discrete categories—while familiar to the public and relatively easy to implement administratively—lend themselves to strategic incentives, even when the design and production processes cannot be changed, and that magnitude of the excess charges can be quite large.

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REFERENCES

Abadie, Alberto and Guido W. Imbens (2006) "Large-Sample Properties of Matching Estimators for Average Treatment Effects," *Econometrica*, 74(1), 235–267. http://dx.doi.org/10.1111/j.1468-0262.2006.00655.x.

Abadie, Alberto and Guido W. Imbens (2008) "On the Failure of the Bootstrap for Matching Estimator," *Econometrica*, 76(6), 1537–1557. http://dx.doi.org/10.3982/ECTA6474.

Abadie, Alberto and Guido W. Imbens (2011) "Bias-Corrected Matching Estimators for Average Treatment Effects," *Journal of Business and Economic Statistics*, 29(1), 1–11. http://dx.doi.org/10.1198/jbes.2009.07333.

Adamou, Adamos, Sofronis Clerides, and Theodoros Zaxhariadis (2014), "welfare Implications of Car Feebates: A Simulation Analysis," *The Economic Journal*, 124(578), F420-F443. http://dx.doi.org/10.1111/ecoj.12094.

AEA (2011), "Report on the implementation of Directive 1999/94/EC relating to the availability of consumer information on fuel economy and CO_2 emissions in respect of the marketing of new passenger cars," prepared for DG-Environment under contract CLIMA.C.2/SER/2011/0002r, Harwell, UK, December.

Alberini, Anna, Markus Bareit, and Massimo Filippini (2014), "Does the Swiss Car Market Reward Fuel Efficient Cars? Evidence from Hedonic Pricing Regressions, a Regression Discontinuity Design, and Matching," FEEM working paper 2014.016, Milan, Italy, February, available at http://www.feem.it/getpage.aspx?id = 6169&sez = Publications&padre = 73

Allcott, Hunt (2011), "Social norms and energy conservation," *Journal of Public Economics*, 95, 1082–1095. http://dx.doi.org/10.1016/j.jpubeco.2011.03.003.

26. 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.

Allcott, Hunt and Michael Greenstone (2012). "Is There an Energy Efficiency Gap?" *Journal of Economic Perspectives,* 26(1), 3–28. http://dx.doi.org/10.1257/jep.26.1.3.

Allcott, Hunt, und Jean-Nathan Wozny (2014), "Gasoline Prices, Fuel Economy, and the Energy Paradox," *Review of Economics and Statistics*, 96(10), 779–795. http://dx.doi.org/10.1162/REST_a_00419.

Anderson, Soren T., Ryan Kellogg and James M. Sallee (2013), "What Do Consumers (Think They) Know About the Price of Gasoline?" *Journal of Environmental Economics and Management*, 66, 383–403. http://dx.doi.org/10.1016/j.jeem.2013.07.002.

Anderson, Soren T., Ian W. Parry, James Sallee and Carolyn Fischer (2011), "Automobile Fuel Economy Standards: Impacts, Efficiency, and Alternatives," *Review of EnvironmentalEconomics and Policy*, 5(1), 89–108. http://dx.doi.org/10.1093/reep/req021.

Angrist, Joshua D., and Jörn-Steffen Pischke (2009),*Mostly Harmless Econometrics. An Empiricist's Companio*n, Princeton, NJ: Princeton University Press.

Andreoni, James (1990), "Impure Altruism and Donations to Public Goods: A Theory of Warm-Glow Giving," *The Economic Journal*, 100(401), 464–477. http://dx.doi.org/10.2307/2234133.

Arguea, Nestor M., and Cheng Hsiao(1993), "Econometric issues of estimating hedonic price functions: With an application to the U.S. market for automobiles," *Journal of Econometrics*, 56(1–2), 243–267. http://dx.doi.org/10.1016/0304-4076(93)90108-H.

Atkinson, Scott E, and Robert Halvorsen(1984), "A New Hedonic Technique for Estimating Attribute Demand: An Application to the Demand for Automobile Fuel Efficiency," *The Review of Economics and Statistics*, 66(3), 417–26. http://dx.doi.org/10.2307/1924997.

Bento, Antonio, Lawrence H. Goulder, Mark R. Jacobsen, and Roger H. von Haefen (2009), "Distributional and Efficiency Impacts of Increased US Gasoline Taxes," *American Economic Review*, 99(3), 667–699. http://dx.doi.org/10.1257/aer.99.3.667.

Berry, Steven, James Levinsohn, and Ariel Pakes (1995), "Automobile Prices in Market Equilibrium," *Econometrica*, 63(4), 841–90. http://dx.doi.org/10.2307/2171802.

Bockstael, Nancy E., and Kenneth E. McConnell (2007), "Environmental and Resource Valuation with Revealed Preferences.A Theoretical Guide to Empirical Models." Dordrecht, The Netherlands: Springer.

Breteau, Vincent and Simon Weber (2013), "Reconsidering the Choice Between Gasoline- and Diesel-Powered Cars. Modeling Demand and Automakers' Reactions,"*Transportation Research Record: Journal of the Transportation Research Board*, 2375, 18–28. http://dx.doi.org/10.3141/2375-03.

Brounen, Dirk, and Nils Kok (2011), "On the economics of energy labels in the housing market," *Journal of Environmental Economics and Management*, 62(2), 166–179. http://dx.doi.org/10.1016/j.jeem.2010.11.006.

Busse, Meghan, Christopher R. Knittel, and Florian Zettelmeyer (2013), "Are Consumers Myopic? Evidence from New and Used Car Purchases," *American Economic Review*, 103(1), 220–256. http://dx.doi.org/10.1257/aer.103.1.220.

D'Haultfoeuille, Xavier, Isis Durrmeyer, and Philippe Fevrier (2013), "The Effect of Public Policies on Consumer Preferences: Lessons from the French Automobile Market," CREST Document de Travail 2013–14, October.

D'Haultfoeuille, Xavier, Pauline Givord, and Xavier Boutin (2014), "The Environmental Effects of Green Taxation: The Case of the French *Bonus/Malus*," *The Economic Journal*, 124(578), F444-F480. http://dx.doi.org/10.1111/ecoj.12089.

Eichholz, P.M.A., N. Kok, and J.M. Quigley (2010), "Doing Well by Doing Good: Green Office Buildings," *American Economic Review*, 100, 2494–2511.

Espey, Molly, and S. Nair (2005), "Automobile Fuel Economy: What is it Worth?" *Contemporary Economic Policy*, 23(3), 317–323. http://dx.doi.org/10.1093/cep/byi024.

Ethier, R.G. ,G.L. Poe, W.D. Schulze, and J. Clark (2000), "A comparison of hypothetical phone and mail contingent valuation responses forgreen-pricing electricity programs,"*Land Economics*, 76, 54–67. http://dx.doi.org/10.2307/3147257.

European Environment Agency (2013), "Monitoring CO_2 Emissions from New Passenger Cars in the EU: Summary of Data for 2012," available at http://www.eea.europa.eu/publications/monitoring-co2-emissions-from-new-cars

Gans, William Lee (2012), The Role of Prices and Information in Residential Energy Consumption and Investment Behavior, PhD dissertation, University of Maryland, College Park.

Gillingham, Kenneth, Richard Newell, and Karen Palmer (2009), "Energy Efficiency Economics and Policy," *Annual Review of Resource Economics*, 1, 597–619. http://dx.doi.org/10.1146/annurev.resource.102308.124234.

Golove, William H. and Joseph H. Eto (1996), "Market Barriers to Energy Efficiency: A Critical Reappraisal of the Rationale for Public Policies to Promote Energy Efficiency," Lawrence Berkeley Laboratory, UC Berkeley.

Goodman, A. C. (1983), "Willingness to pay for car efficiency: A hedonic price approach," *Journal of Transport Economics and Policy*, 17(3), 247–266.

Greenstone, Michael, Elizabeth Kopits and Ann Wolverton (2013), "Developing a Social Cost of Carbon for US Regulatory Analysis: A Methodology and Interpretation," *Review of Environmental Economics and Policy*, 2013, 7(1), 23–46. http://dx.doi.org/10.1093/reep/res015.

Hahn, Jinyong, Petra Todd, and Wilmert van der Klaauw (2001), "Identification and Estimation of Treatment Effects with a Regression-Discontinuity Design," *Econometrica*, 69(1), 201–209. http://dx.doi.org/10.1111/1468-0262.00183.

Hassett, Kevin A., and Gilbert E. Metcalf (1993), "Energy Conservation Investment: Do Consumers Discount the Future Correctly?" *Energy Policy,* 21(6), 710–716. http://dx.doi.org/10.1016/0301-4215(93)90294-P.

Heckman, James J., Hidehiko Ichimura, and Petra Todd (1998), "Matching as an Econometric Evaluation Estimator," *Review of Economic Studies*, 65, 261–294. http://dx.doi.org/10.1111/1467-937X.00044.

Houde, Sebastien (2014a), "How Consumers Respond To Environmental Certification And the Value of Energy Information," NBER working paper 20019, Cambridge, MA, March.

Houde, Sebastien (2014b), "Bunching with the Stars: How Firms Respond to Environmental Certification," draft manuscript, University of Maryland, College Park, May (available at http://terpconnect.umd.edu/˜shoude/EnergyStarFirms-Houde_May2014.pdf).

Huse, Cristian, and Claudio Lucinda (2014), "The Market Impact and Cost of Environmental Policy: Evidence from the Swedish Green Car Rebate," *The Economic Journal*, 124(578), F393-F419. http://dx.doi.org/10.1111/ecoj.12060.

Imbens, Guido W., and Thomas Lemieux (2008), "Regression discontinuity designs: A guide to practice," *Journal of Econometrics*, 142(2), 615–635. http://dx.doi.org/10.1016/j.jeconom.2007.05.001.

Imbens, Guido and Karthik Kalyanaraman (2012), "Optimal Bandwidth for the Regression Discontinuity Estimator," *Review of Economic Studies*, 79(3), 933–959. http://dx.doi.org/10.1093/restud/rdr043.

IPCC (2007), "Climate Change 2007: Synthesis Report. Contribution of Working Groups I, II and III to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change." [Core Writing Team, Pachauri, R.K and Reisinger, A. (eds.)]. IPCC, Geneva, Switzerland, pp. 104

Ito, Koichiro, and James Sallee (2013), "The Economics of Attribute-based Regulation: Theory and Evidency from Fuel Economy Standards," draft paper, Boston University, Boston, November 2013, available at http://people.bu.edu/ito/attributes.pdf

Jacobsen, Grant D., Matthew J. Kotchen, Michael P. Vanderbergh (2012), "The Behavioral Response to Voluntary Provision of an Environmental Public Good: Evidence from Residential Electricity Demand," *European Economic Review*, 56, 946–960. http://dx.doi.org/10.1016/j.euroecorev.2012.02.008.

Jaffe, Adam B. and Robert N. Stavins (1994), "The Energy Efficiency Gap. What Does It Mean?" *Energy Policy*, 22(10), 804–810. http://dx.doi.org/10.1016/0301-4215(94)90138-4.

Knittel, Christopher R. (2011), "Automobiles on Steroids: Product Attribute Trade-Offs and Technological Progress," *American Economic Review*, 101, 3368–3399. http://dx.doi.org/10.1257/aer.101.7.3368.

Kotchen, Matthew J. (2009), "Voluntary Provision of Public Goods for Bads: A Theory of Environmental Offsets," *The Economic Journal*, 119, 885–889. http://dx.doi.org/10.1111/j.1468-0297.2008.02215.x.

Kotchen, Matthew J and Michael R. Moore (2007) "Private provision of environmental public goods: Household participation in green-electricity programs*", Journal of Environmental Economics and Management*, 53, 2007, 1–16. http://dx.doi.org/10.1016/j.jeem.2006.06.003.

Lee, David S., and Thomas Lemieux (2010), "Regression Discontinuity Designs in Economics," *Journal of Economic Literature*, 48(2), 281–355. http://dx.doi.org/10.1257/jel.48.2.281.

Matas, Anna, and Josep-Lluis Raymond (2009), "Hedonic prices for cars: an application to the Spanish car market, 1981–2005," *Applied Economics*, 41(2), 2887–2904. http://dx.doi.org/10.1080/00036840701720945.

Newell, Richard G. and Juha V. Siikamäki (2013),"Nudging Energy Efficiency Behavior: The Role of Information Labels," NBER Working Paper 19224, Cambridge, MA, July.

Mabit, Stefan L. (2008), "Vehicle Type Choice Under the Influence of A Tax Reform and Rising Fuel Prices," *Transportation Research Part A*, 64, 32–42. http://dx.doi.org/10.1016/j.tra.2014.03.004.

McCrary, Justin (2008), "Manipulation of the running variable in the regression discontinuity design: A density test,"*Journal of Econometrics*, 142(2). 698–714. http://dx.doi.org/10.1016/j.jeconom.2007.05.005.

Murray, Jonathan, and Nicholas Sarantis (1999), "Price-Quality Relations and Hedonic Price Indexes for Cars in the United Kingdom," *International Journal of the Economics of Business*, 6(1), 5–27. http://dx.doi.org/10.1080/13571519984287.

Nair, Santosh, and Molly Espey (2004), "Automobile Fuel Economy: What is it Worth?" paper presented at the 2004 Annual meeting of the American Agricultural Economics Association, Denver, CO, August.

Rosen, Sherwin (1974), "Hedonic Prices and Implicit Markets: Product Differentiation in Pure Competition," *Journal of Political Economy*, 82(1), 34–55. http://dx.doi.org/10.1086/260169.

Sallee, James M., Sarah E. West, and Wei Fan (2011), "The Effect of Gasoline Prices on the Demand for Fuel Economy in Used Vehicles: Empirical Evidence and Policy Implications," unpublished manuscript.

Sallee, James M. (2013), "Rational Inattention and Energy Efficiency," NBER working paper 19545, Cambridge, MA, October.

Tonozzi, Franco (2007), "Dieselautos: UnterdemStrichteureralsBenziner," available at http://www.ktipp.ch/artikel/d/dieselautos-unter-dem-strich-teurer-als-benziner/

Turrentine, Thomas S., and Kenneth S. Kurani (2007), "Car Buyers and Fuel Economy?" *Energy Policy*, 35, 1213–123. http://dx.doi.org/10.1016/j.enpol.2006.03.005.

UK Department of Energy and Climate Change (2009), "Carbon Valuation in UK Policy Appraisal: A Revised Approach Climate Change Economics," UK Department of Energy and Climate Change, July 2009.

Williams, Roberton C. and Sarah West (2005), "The Cost of Reducing Gasoline Consumption," *American Economic Review*, 95(2), 294–299. http://dx.doi.org/10.1257/000282805774669673.

Witt, Robert (1997), "The Demand for Car Fuel Efficiency: Some Evidence for the UK," *Applied Economics*, 29(9), 1249–1254. http://dx.doi.org/10.1080/00036849700000015.