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Could the sufficiency of vehicles be used to apply a progressive and large-scale car fee at the city level?

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Abstract

Policies conducted by cities to tackle the downsides of car traffic have little progressivity. Most of the time no differentiation is made based on the characteristics of a vehicle. By contrast, car policies at national or supranational levels are often modulated based on the weight of a vehicle, its CO_2 emissions, *etc.* Besides, an often forgotten distinction exists between a vehicle's efficiency and its sufficiency. The former quantifies how good a vehicle is at turning the energy it has into the energy it needs. The latter quantifies how much energy it needs. Both are important regarding the environmental performance of a vehicle, yet sufficiency draws less attention. In this work we compare the potentials of progressive car fees indexed on various car characteristics in terms of environment, use of space and equity chiefly. We find that sufficiency-based car fees have the potential to target the CO_2 emissions of vehicles almost as well as CO_2-based fees while charging large and expensive vehicles more consistently. This also means that small and cheap vehicles would more consistently be charged less than in a CO_2-based scheme. This difference is especially significant given that public acceptance is often the main hurdle when implementing a road charging program. Once implemented, a sufficiency-based charge may give a lot of flexibility to cities for dealing with their cars, and have positive synergies with other transport policies.

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2WD, 4WD	2-wheel drive, 4-wheel drive
ADAC	Allgemeiner Deutscher Automobil-Club
EUDC	Extra-Urban Driving Cycle
HVF	Heavy Vehicle Fee
ICE	Internal Combustion Engine
KBA	Kraftfahrt-Bundesamt
LCV	Light commercial vehicle
LEZ	Low Emission Zone
NEDC	New European Driving Cycle
PEV	Plug-in Electric Vehicle
UDC	Urban Driving Cycle

Introduction

Dense traffic brings congestion and pollution in many city centres around the world. Prospective scenarios tend to show that mid-term technology and policy improvements, though significant, won't alone compensate the side-effects (in terms of fuel consumption, emissions and congestion) associated with a steady growth in veh.km travelled worldwide until 2050. Dynamic sets of car-related policies are thus much needed to reconcile transport activities and sustainability.

When it comes to the emissions and consumption of vehicles, an important distinction can be made between a vehicle's efficiency and its sufficiency. Sufficiency refers to the amount of energy that is required at the wheel to overcome drag and inertia and thus move the vehicle. It depends on only three characteristics of a vehicle: its aerodynamic drag, its tyre resistance, and its weight. Efficiency on the other hand refers to how efficiently energy is converted from potential energy present in the tank to energy at the wheel, and thus depends on the type of powertrain used. In Europe it has been estimated that between 1990 and 2010, 50% of the efficiency improvements of cars have been offset by increases in the average size of vehicles, i.e. decreases in their sufficiency.

Making our vehicles more sufficient, by for example reducing the average weight of our cars, could have numerous advantages. Like efficiency-related improvements, it would lead to a decrease, all things being equal, of the emission and consumption levels of cars. Unlike efficiency-related improvements, it doesn't require new technologies, and makes cars cheaper. At first sight it would be especially valuable in city centres around the world, where private passenger vehicles, most of the time occupied by a single person, raise problems regarding pollution, the use of space, and congestion.

However policies introduced by cities to tackle the downsides of car traffic have little progressivity, in the sense that vehicles are mostly targeted regardless of their size, weight or emissions. The present research aims to propose and investigate a family of car policies that could be implemented in urban contexts, using vehicle characteristics to modulate a progressive car fee at the city scale. We want to assess which vehicle characteristics would best be used to index such a progressive fee, with an emphasis put on sufficiency characteristics.

In chapter 1, we give an overview of the trends and policies related to cars worldwide. In chapter 2, we present typical policies that are implemented by cities to deal with their cars. Chapter 3 is dedicated to further introduce the distinction between efficiency and sufficiency. In chapter 4 the procedure followed to gather the dataset we use is described, while in chapter 5 we define typical objectives of car policies in an urban context and their metrics. In chapter 6, we select vehicle characteristics whose potential regarding the objectives defined in chapter 5 is further investigated in chapter 7. Finally chapter 8 gives an outlook on the issues surrounding the effective implementation of a progressive car charge.

Part I

Context and problematic

Chapter 1

Global trends and policies associated with cars

1.1 The bright future of road transport

The current development of the transport sector worldwide is impressive, and road passenger transport is no exception. Between 2000 and 2009 only, the total length of paved roadways (measured in lane-km) has increased by more than 35%. Much of this growth originates in developing countries, with China and India accounting for more than 50% of the additions (DULAC 2013).

The forecasted trends for the next decades are just as dramatic. According to the IEA and their MoMo mobility model (DULAC 2013), paved roadway length is expected to increase by another 60% between 2010 and 2050, in the most likely scenario. Again this global trend hides strong disparities between developed and developing countries. While China and India are still expected to account for half of the growth, it is estimated that paved roadway lengths could slightly decrease in Japan and Germany.

Despite this strong expansion of road networks in developing countries, it is expected that Chinese and Indian roads will get more and more saturated, as traffic growth outpaces road construction. This trend, illustrated by the forecasted road occupancy levels presented on figure 1.1, may be especially problematic in urban centers.

Even if such long-term estimations should be taken with care, they all suggest a strong near-term and mid-term increase in the number of cars at the global level. Although this evolution can be considered positive and a logical consequence of the fast economic development of many countries, countries around the world are faced with a great challenge to cope with the downsides of private vehicle transport: energy consumption, pollution, congestion, space occupation and livability in the cities.

1.2 National and supranational policies

To mitigate the environmental impacts of a flourishing vehicle park at the national level, a range of policies are considered by many as being particularly efficient (IEA 2012) (MIT 2009). These

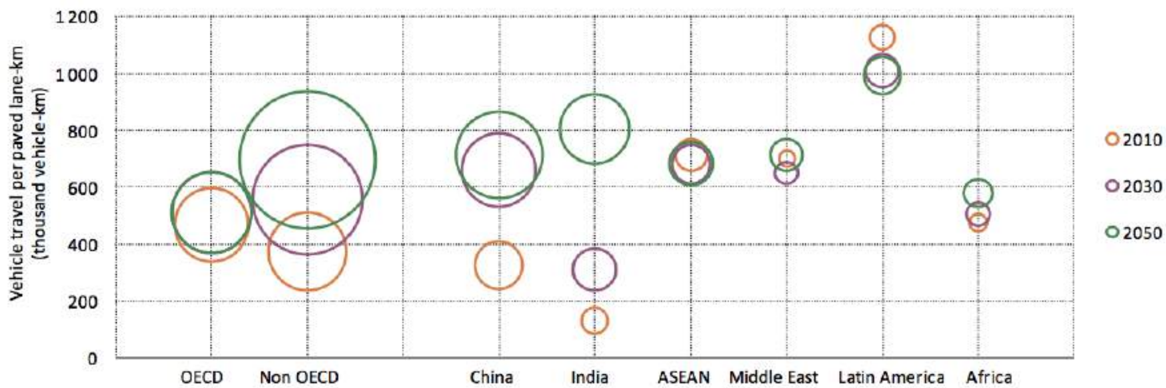

Figure 1.1: Worldwide road occupancy levels and their predicted evolution. Source: (DULAC 2013)

policies are the following:

- a clear labelling of fuel economy and CO_2 emission to guide consumers when they buy a vehicle,
- stringent fuel economy and CO_2 emission standards,
- a tax increase on motor vehicle fuels,
- vehicle taxes at the point of purchase, for example a feebate incentive system based on vehicle consumption.

To illustrate how countries or unions apply these ideas, we give next an overview of the policies implemented in various parts of the world.

National and supranational governments are setting standards for new vehicles. Among these policies, fuel economy standards are praised for their efficiency and widely adopted. They were first introduced in 1975 in the USA after the Arab Oil Embargo, as a way to improve the fuel economy of new cars. The ones existing nowadays are summarized in table 1.1, showing the various targets and standard designs in the countries or region where they exist, as well as the size of each car market in 2013.

Some designs target GHG emissions (target unit in gCO_2e/km), others target CO_2 emissions (target unit in gCO_2/km), and others target fuel consumption. The "adjustment factor" column gives the car characteristic that is used to set different targets for different car-makers. In the case of Europe for example, CO_2 targets are adjusted for each car-maker depending on the average weight of the models they sell. Fiat, whose corporate average is 1209 kg, has a target of 89 gCO_2/km by 2020, while Daimler, whose corporate average is higher at 1583 kg, has a target of 101 gCO_2/km. Footprint[1] is one common measure of the surface occupied by a vehicle and it is used in Canada and in the US as the adjustment factor.

Be it for weight-based or footprint-based designs, the idea is that without such an adjustment car-makers that are selling heavier or bigger cars would have to do important efforts to meet

[1] Two definitions of a vehicle's surface are commonly used: the *pan area* or *shadow*, simply equal to width times length of the vehicle; and the *footprint*, equal to width times wheelbase, the distance between the two axes. Throughout this work "surface" refers to pan area.

Country or region	Target year	Unadjusted fleet target	Adjustment factor	New sales in 2013 (million)
United States	2025	4.2 L/100km or 88 gCO_2e/km	Footprint	8.0
Canada	2025	98 gCO_2e/km	Footprint	0.8
Mexico	2016	6.0 L/100km or 140 gCO_2e/km	Footprint	0.7
Brazil	2017	5.7 L/100km	Weight	3.0
European Union	2021	95 gCO_2/km	Weight	11.8
Japan	2020	4.9 L/100km	Weight	4.6
South Korea	2020	97 gCO_2e/km	Weight	1.2
China	2015	6.9 L/100km	Weight	17.9
India	2021	113 gCO_2/km	Weight	2.5

Table 1.1: Market size and fuel economy standards in different parts of the world, derived from (ICCT 2014)

the target, while car-makers selling lighter or smaller cars would already meet or be close to the target. Thus adjusted structures are used to avoid a distortion of the competition between car-makers and to encourage all of them to improve the environmental performance of their vehicles (P Mock 2011).

Yearly taxes on cars are also in place in many countries. In Finland for instance owners of gasoline cars pay a yearly tax whose amount is linearly increasing with the CO_2 emissions of the vehicle, while for owners of diesel cars the tax linearly increases with CO_2 emissions and weight. In Germany a yearly tax is levied which increases linearly with the power and the CO_2 emission level of a vehicle, and numerous other examples exist.

An example of a tax levied at the time of purchase, in France a feebate on new vehicles exists since 2008: vehicles with low CO_2 emissions receive a rebate, vehicles with high emissions are taxed, and the rates are calculated to obtain a balanced budget. In this case the rebate and tax levels increase non-linearly with CO_2 levels, as shown by table 1.2. Also implemented in other European countries, these taxes have always coincided with significant sales shifts towards low-emitting vehicles, even if due to the concurrent economical crisis it is difficult to draw definitive conclusions (IEA 2012). Figure 1.2 presents the emission levels of new sales at the EU25 level and in countries where a purchase tax based on CO_2 was introduced. Although a decrease is globally observable at the EU25 level, stronger decreases are observed around the year of introduction in the countries where a purchase tax was implemented.

CO_2 emissions (gCO_2/km)	Purchase feebate
$0 <$ CO_2 < 20	-6 300 €
$21 <$ CO_2 < 60	- 4 000 €
$131 <$ CO_2 < 135	150 €
$136 <$ CO_2 < 140	250 €
$141 <$ CO_2 < 145	500 €
$146 <$ CO_2 < 150	900 €
$151 <$ CO_2 < 155	1 600 €
$156 <$ CO_2 < 175	2 200 €
$176 <$ CO_2 < 180	3 000 €
$181 <$ CO_2 < 185	3 600 €
$186 <$ CO_2 < 190	4 000 €
$191 <$ CO_2 < 200	6 500 €
$201 <$ CO_2	8 000 €

Table 1.2: Bonus-malus when purchasing a vehicle in France in 2015. Source: (MEDDE 2015)

Fuel economy or CO_2 emission labels have also been introduced in many countries, including the USA, Japan, China, India and EU countries. They have various designs. Some show an absolute information on environmental performance, while others display a relative information, with vehicles ranked within their weight category for example. They should help car purchasers in making more informed decisions.

All in all at the national and supranational scales diverse policies are used to influence the car market or raise revenues. However all have in common that they are somehow indexed on one or another characteristic of the vehicle, like its CO_2 emission level, its power, its weight, *etc.* In this sense national and supranational policies are differentiated, which as we will see is not the case for most car policies conducted by cities.

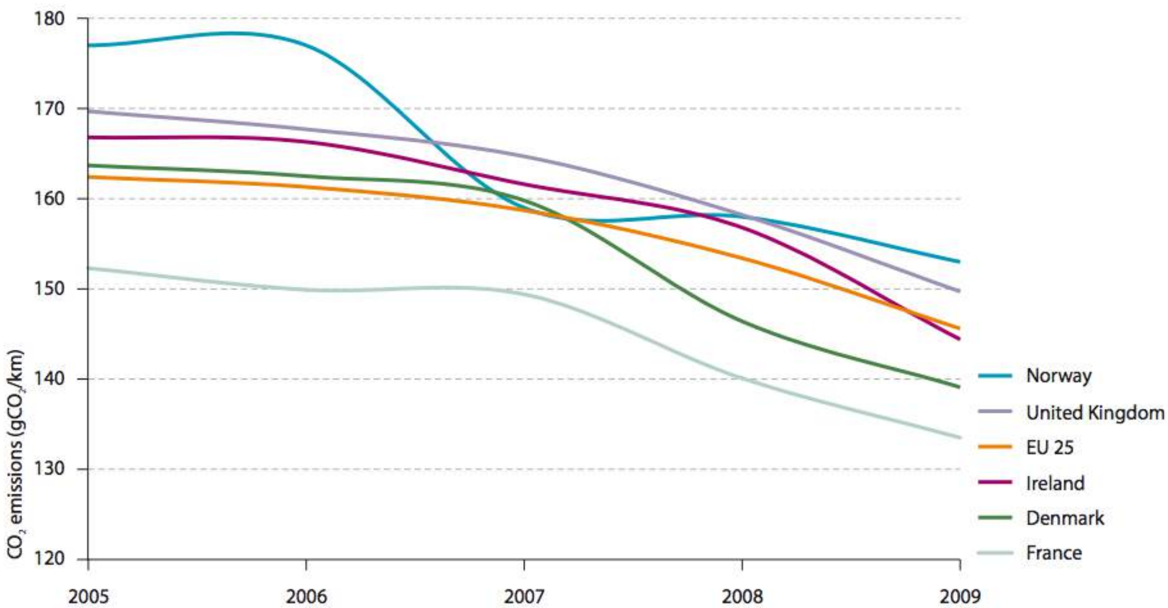

Figure 1.2: Year of introduction of a purchase tax: Norway 2007, UK 2010, Ireland 2008, Denmark 2007, France 2008. Source: (IEA 2012)

Chapter 2

The cities and their cars

2.1 Urban policies related to cars

Very diverse policies are being pursued by cities around the world to mitigate the downsides of private vehicles. Among those, some aim at providing attractive alternatives to private vehicles, others put restrictions on their use, and others provide incentives for the use of greener vehicles. In this section we give an overview of these trends in urban transport policies by presenting projects conducted by various cities worldwide.

2.1.1 Pull policies

Among policies aimed at providing attractive alternatives to private vehicles, the development of public transport systems is one of the most important. Creation or extension of metro lines, tramway lines, bus lines are underway in numerous cities, often as part of a larger plan for sustainable transport.

Among the abounding examples is the “Connected Birmingham” initiative launched by the city of the same name in 2014, with the following goals: make the transport of goods and persons across the city more equitable, more efficient and more sustainable, improve public health and make Birmingham more attractive. To achieve these goals, the 20-year plan aims at the construction of at least three metro lines, nine inter-city bus rapid transit lines, and the reopening and upgrading of rail routes, along with numerous additional measures (encouraging walking and cycling, a Low Emission Zone (LEZ) in the city centre, redirecting through traffic onto a substantially upgraded ring road, park and ride facilities, *etc.*).

Some cities also experiment with new forms of flexible public transport made possible by the use of digital technologies. The city of Helsinki started an innovative pilot project in 2013, consisting in a fleet of 15 nine-seater minibuses (figure 2.1). The originality is that the routes followed by the buses are constantly updated to best fit with the traveller demand, calculated after the latter enter their place of departure, destination and desired departure time on their phone. Such a system may achieve the best of both worlds, by combining the point-to-point freedom that the car offers with the affordability and sustainability of public transport. In Helsinki the project is still in its infancy, but it shows yet another bold public transport initiative conducted by a city to provide alternatives to the private car.

Figure 2.1: Kutsuplus are nine-seaters buses whose route is constantly updating based on passenger demand. Source: kutsuplus.fi

Another way to lessen the use of private cars is to encourage active modes, i.e. cycling and walking. In London for instance, an ambitious plan aimed at upgrading the road network was unveiled at the end of 2014. London's Road Modernisation Plan (TfL 2014a) has a total budget of £4 billion until 2021. The biggest share of this budget is allocated to road assets renewals and refurbishments, with £1.8 billion. However it is worth noticing that the second largest item of expenditure is cycling infrastructure (£900 million), before road enhancements (£600 million). Measures to improve cycling conditions include changes at 33 major junctions for easier crossing, cycle superhighways and other new bike lanes, forming a "Tube network for the bike", as well as 80 000 additional cycle parking spaces.

Another trend in urban areas is the introduction of sharing systems, that have undergone a rapid expansion lately. The number of bike sharing systems has skyrocketed in the last decade, from 13 in 2004 to more than 850 in 2015 (Fishman 2015). The systems are located all around the world, including in developing countries. China alone counts more than 230 for example.

Car-sharing systems, which in contrast to bike-sharing systems are often operated by private companies, are also expanding at a dramatic pace. Various approaches exist (Barth and Shaheen 2002), and distinctions are often made between station-based systems, for which the user has to let his car where he picked it; free-floating systems, that allow the user to let his car where he wants and thus perform one-way trips; and peer-to-peer car-sharing whereby car owners make their vehicle available for others to rent. These systems are expected to make flexible transport more affordable, to reduce the amount of parking spaces needed in a city, to improve air quality and to promote the use of public transport.

Car2go for example, founded in 2008 by Daimler, is the largest operator of free-floating car sharing systems and has grown considerably since its inception, with 13 500 cars disseminated in 30 cities in Europe and North America as of 2015.

Another successful example is Autolib', a free-floating system started in 2011 in Paris with fully

Figure 2.2: Artist view of an improved junction in London, a particular emphasis is given to biking. Source: Transport for London

electric vehicles and dedicated parking spaces. It is operated by the Bolloré group, while political decisions, for example related to the installation of new stations, are taken within Autolib' Métropole, an entity gathering cities around Paris willing to participate in the scheme. Counting 250 cars at its launch, the system rely in 2015 on more than 3000 vehicles spread over almost 1000 stations located in the 86 participating cities (Autolib-Métropole 2015). The number of registrations is also rising sharply, as indicated by figure 2.3.

Interestingly these forms of mobility relying on shared vehicles are blurring the distinction between public and private transport and are made possible by the extensive use of digital technologies. Another perspective opened by the advance of technologies is the use of autonomous vehicles (figure 2.4), which may sooner or later revolutionize urban mobility (Spieser et al. 2014). For example researchers of the MIT have estimated that using an on-demand fleet of 300 000 autonomous vehicles, it would be possible to serve the whole population of Singapore, while today 800 000 private cars serve 12% of the population. These contrasting numbers show the potential of such systems, although the authors warn that the scenario they describe may not be the best way to make use of autonomous vehicles, as it could reinforce the dependency to automobile and its consequences.

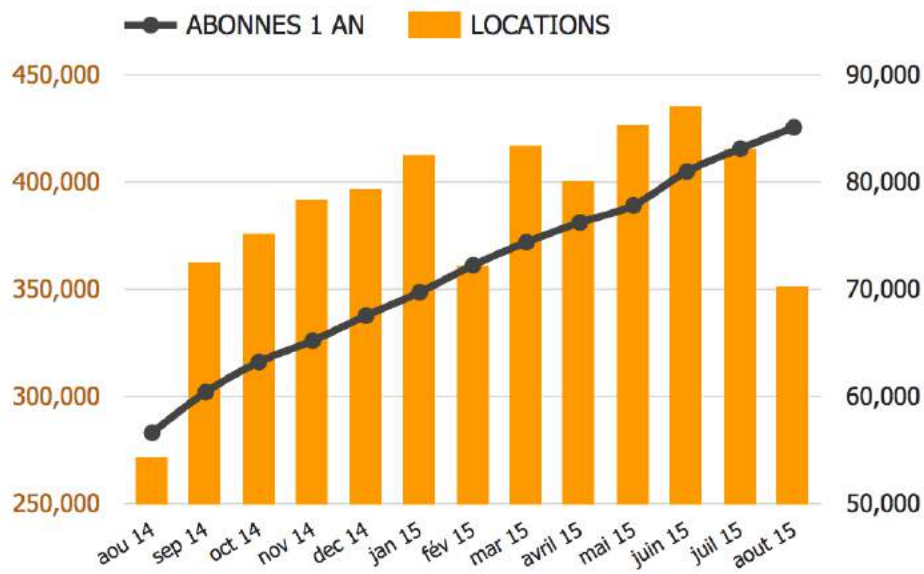

Figure 2.3: Black dotted line: yearly subscriptions to Autolib. Orange bars: monthly car rentals. Source: (Autolib-Métropole 2015)

2.1.2 Push policies

In addition to providing attractive alternatives to the use of private vehicles, cities have the possibility to restrict the use of cars to various extents. One example of such a policy is congestion charging, which is considered the first-best option to account for the costs of congestion by neoclassical economic theories (Jeanrenaud 1999). More generally, road charging is used by a few cities to tackle congestion or environmental issues.

Stockholm is among the cities that have successfully implemented congestion charging. After a trial period started in 2006, the scheme was permanently approved by referendum in 2007. Strong evolutions were reported by the city of Stockholm at the end of the trial period (Stad 2006). A relief of congestion was observed, with a 22% reduction of traffic at peak hours and a 30% to 50% decrease in queueing times. It was also observed that congestion charging had wider impacts, with a decrease of 14% in veh-km travelled in the inner city, leading to a similar reduction in emissions of carbon dioxide and other air pollutants.

Milan has introduced an environmental charging scheme in 2008 ("Ecopass"), taking the form of urban tolls with rates varying based on the emission standard of a vehicle. In the months following the introduction of the Ecopass program, a 12% decrease in the number of vehicles entering the restricted zone has been observed, along with a 4% increase in travel speed. Regarding the environment, a sharp change in the composition of the fleet of vehicles entering the city has been reported, with a 50% decrease in the number of polluting vehicles subject to the charge, compared to the months prior to its introduction (Milano 2008). This environmental charging scheme has been replaced by a more conventional congestion charging scheme in 2012[1].

Another policy restricting the use of private vehicles consists in banning certain cars from given

[1] The reasons for this shift are discussed in (8.2).

Figure 2.4: The Google car. Autonomous vehicles may profoundly alter mobility forms. Source: Google

areas based on their emission level. In Europe, Low-Emission Zones (LEZ) have been implemented in almost 200 cities over the last two decades, mostly in Italy and Germany (figure 2.5). Their goal is to reduce pollution levels in cities to meet European targets (ADEME 2014). Implementations vary between cities, but the principle remains the same: categories of particularly polluting vehicles are not allowed to enter specific areas. In some countries only buses and lorries are concerned, in Germany light vehicles are also concerned, and in Italy even two-wheelers have to comply with certain criteria. The extent of the protected areas also vary, from 2 km^2 in Illsfeld (Germany) to 1500 km^2 in London.

Parking policies are another major family of push policies. They can take various forms: parking permits, parking pricing, car-free developments, *etc.* In London for example the London Plan, defining the spatial development strategy of the city, sets out minimum cycle parking and maximum car parking standards (Mayor-of-London 2015). In the case of residential developments for instance, the upper limit is based on the number of beds in the new household, and it is furthermore specified that 20% of car spaces should be for electric cars, and that the number of spaces built should be significantly decreased in areas of good public transport accessibility.

In China, where many cities are overflowing with cars, more radical restrictive measures have been introduced, in the form of auctions, resulting in registration prices that can exceed the price of the vehicle, or lotteries, where the odds of winning are very low. In Beijing for instance the probability of winning a plate was less than 1% in 2013 (Wan, Daniel Sperling, and Wang 2015). In Guangzhou and Tianjin, where hybrid systems are used, it was 2-3%, with the additional possibility to pay $2100 to $2600 to buy a plate.

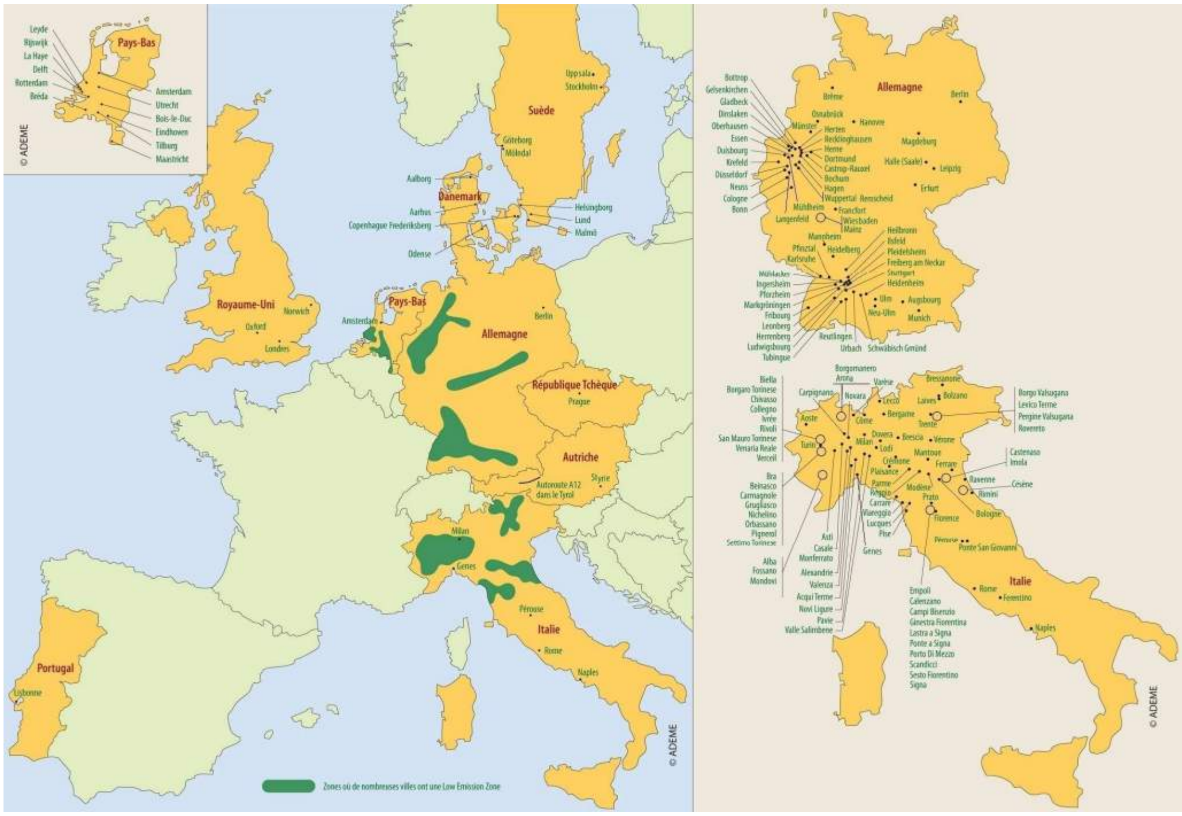

Figure 2.5: Low emission zones (LEZ) across Europe. Most are located in Italy and Germany. Source: (ADEME 2014)

2.1.3 Greener vehicles

Many cities also seek to encourage the use of greener vehicles to address the issues of pollution and GHG emissions. As an illustration, from 2009 many Chinese cities have introduced ambitious policies to favor plug-in electric vehicles (PEV), as part of the national program “Ten Cities, Thousand Vehicles” (Wan, Daniel Sperling, and Wang 2015). Subsidies of up to $9200 per vehicle were offered by the central government, with many local governments providing further incentives, in the form of subsidies or free registration plates. In Shanghai it is estimated that in total the incentive amounted to over $27 000.

Oslo has introduced a wide range of incentives to foster the use of electric cars. In the Norwegian capital, they are exempt from import and value-added taxes, from road and ferry tolls and from parking fees. They can be used on dedicated bus lanes. The electricity to charge their batteries is provided for free by the city of Oslo, they have lower insurance costs, and the installation of home charging stations is subsidized. Added together, these measures have had a large impact on electric vehicles sales. As shown on figure 2.6, in 2012 Norway was by far the country with the highest share of electric vehicles in new car sales (Hannisdahl, Malvik, and Wensaas 2013).

Cities are thus already relying on a wide variety of policies to address the downsides of a mobility primarily based on the use of private cars, with encouraging results and sometimes success stories. In inner London for example, traffic has been reduced by 30% in the last decade and

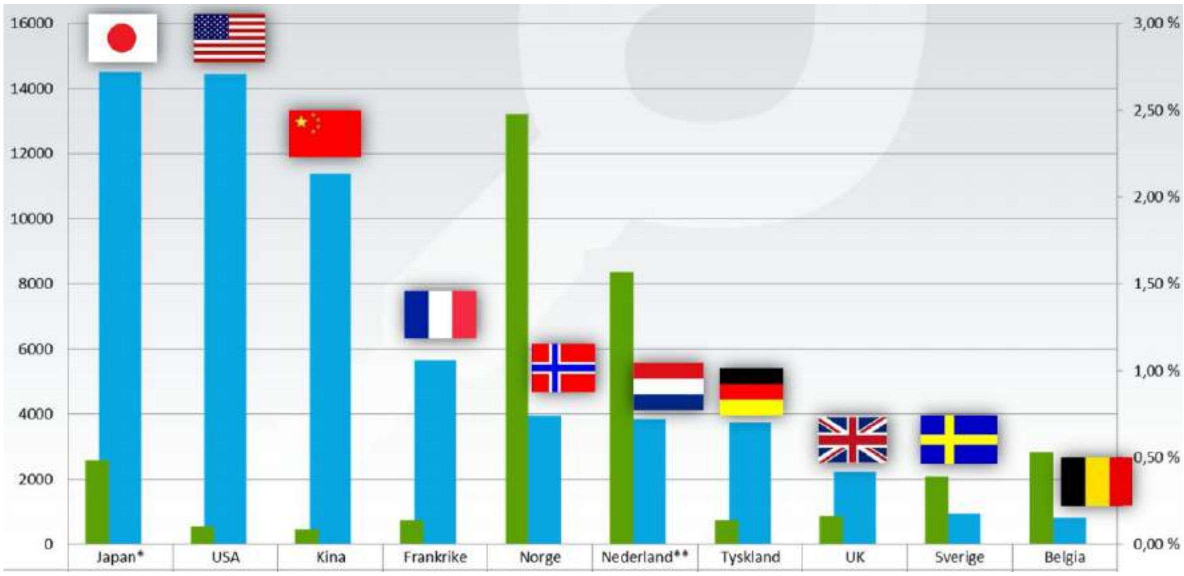

Figure 2.6: Absolute (blue) and relative (green) electric vehicle sales in different countries. Norway has the highest share by far. Source: (Hannisdahl, Malvik, and Wensaas 2013)

private cars have a modal share of 15% only. However and as we will see in the next part, there are trends and forecasts suggesting that cars may yet continue to crowd many cities for many more years.

2.2 Time horizon to low-energy urban mobility

Parallel to the development of policies aimed at mitigating the impacts of cars in urban areas, a decrease in vehicle-kilometer travelled has been observed in a number of cities of mature countries (Newman and Kenworthy 2011), and the phenomenon has given rise to the “peak car” concept. There is no consensus on the reasons behind this phenomenon, although factors such as changing urban cultures, growth in public transport and high fuel prices have been advanced. Albeit suggesting that the downsides of cars may not remain a problem for long in cities, the “peak car” observation is limited to relatively few cities of the developed world.

Tim Schwanen argues that even in developed countries, the perspective of rapid changes through bike and car sharing systems, the reallocation of road space, self-driving cars and the like may be over-optimistic (Schwanen 2015). Historical paths and investments, vested interests, regulatory obstacles and consumer inertia are hurdles that may significantly slow down the transition to new forms of urban mobility.

In the growing markets of the developing world the picture is way different from what is observed in the mature markets of the developed countries. In China, besides a rapid expansion of road infrastructure (see 1.1), the number of private vehicles is expected to continue growing fast, from 18 million in 2010 to 280 million in 2020, compared to 1.4 million in 1990 (Cahill, Taylor, and Dan Sperling 2013). Although these numbers should be taken with care given the volatility of the Chinese car sales and the global economy as a whole, such a terrific predicted growth certainly shows that cars have a bright future globally. Simulations from the OECD even predict an increase of the car modal split worldwide, from less than 50% in 2000 to 60% in 2050 (OECD 2011).

Naturally urban areas in developing countries follow similar trends. Veh-km travelled are growing rapidly within major urban areas in China, at 10% per year in 2012 (Zhao et al. 2012). Moreover, the modal share of non-motorised modes is declining in favor of public and private motorised modes. Cycle modal share is still high in all major cities, 40% for instance in the city of Jinan, but these shares are rapidly decreasing.

The possibility that a large portion of these new cars will be partly electric also seem to be over-optimistic. In China, an ambitious plan was launched in 2009 (see 2.1.3) granting large subsidies for the purchase of plug-in electric vehicles (PEV), with the objective that PEV account for 10% of car sales by 2012. However in 2013, PEV represented less than 0.1% of vehicle sales (Wan, Daniel Sperling, and Wang 2015). This failure of the plan illustrates the difficulty of achieving a high share of battery-powered vehicles in many car markets. Overall, the IEA estimates that electric vehicles sales will be multiplied by more than a hundred by 2020, i.e. only 2% of car sales (Trigg et al. 2013). Although largely improved, internal combustion engines (ICE) are likely to continue dominating the car market worldwide (Berggren and Magnusson 2012). As stated in (Zhao et al. 2012):

> “ The projected growth in motorisation however remains rapid across all major urban areas in China. Avoiding the move towards carbon intensive travel – based largely on the ICE petrol car – will be extremely difficult. ”

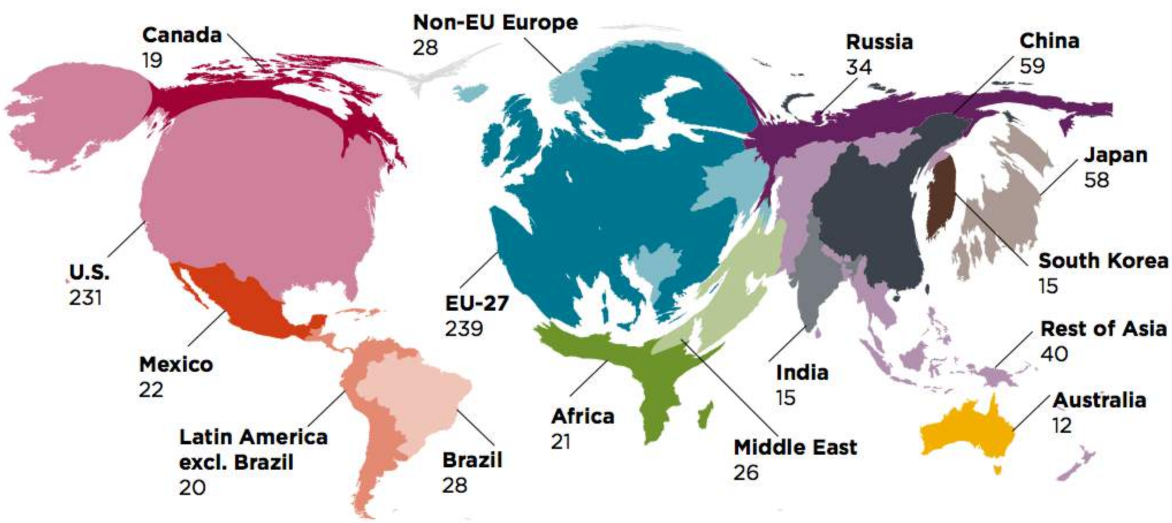

Figure 2.7: Light-duty vehicle stock in 2010 (in million). Source: (Peter Mock 2013)

With the rapid urbanisation of the world, the largest part of humanity’s consumption occurs in urban contexts. Globally, cities already account for 75% of the energy consumption and 80% of greenhouse gases emissions (Zhao et al. 2012). In this context, urban planners and their policies have a decisive role to play. As there is also no straightforward cure to the current problems posed

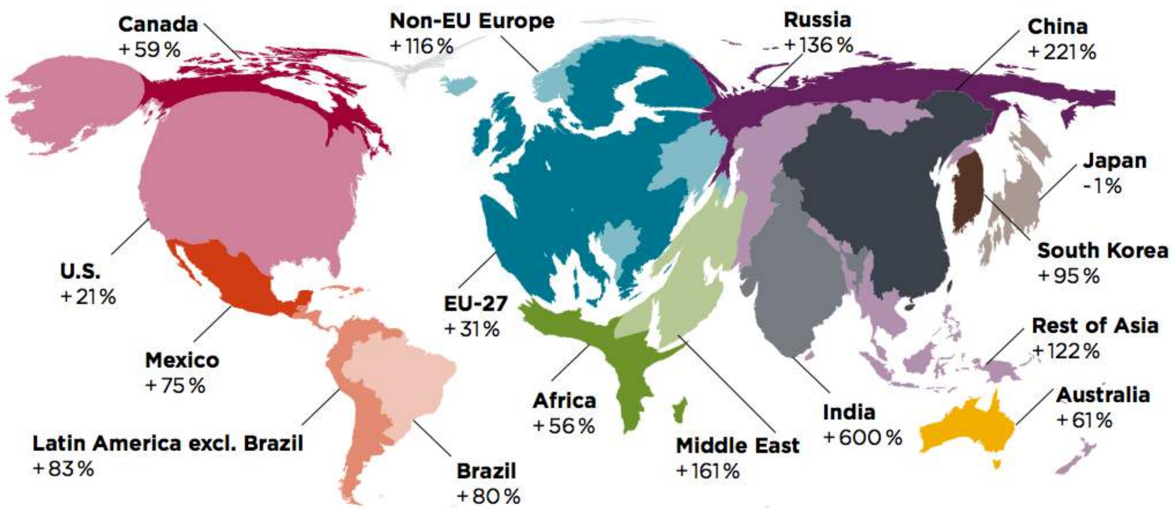

Figure 2.8: Predicted light-duty vehicle stock in 2030 (% change compared to 2010). Source: (Peter Mock 2013)

by private vehicles in urban areas, we want to discuss another kind of policy that could be added to the toolbox of city planners.

Chapter 3

The potential of sufficiency

3.1 Progressive car policies at the city-level

City policies directly related to private cars don't have the progressivity of national policies. Many are based on a regulation of the use of space: Low Emission Zones, parking policies, car-free new developments, extension of pedestrian zones, etc. These policies can't realistically be extended in a very ambitious way. For example, pedestrian areas are often limited to relatively small portions of an urban area, like the historical city center. LEZ can have larger perimeters, but only very polluting vehicles are excluded (ADEME 2014). Restriction policies that would concern all the vehicles present in the entire area of a city would put too much constraints on the transport system to be accepted. Similarly, incentives provided by cities for green vehicles only concern a small number of efficient vehicles, as providing generous subsidies for a significant share of the car sales would be too costly.

Congestion charging as an urban policy goes in the direction of having a more global impact on all cars at the city-scale. Although the idea is old, it has been implemented in only few cities, most notably London, Singapore, Stockholm and Milan. Proposals have been rejected in other cities, like Hong-Kong, New York or Manchester. More than technical obstacles, public acceptance is one of the main hurdles to practical implementations, with questions of equity and justice playing an important role in the formation of the public's perception (Souche, Raux, and Croissant 2012).

Road charging schemes are policies where a differentiated charge holds promise. But in the existing congestion schemes the charge is a flat rate applied to all cars[1] irrespective of their characteristics[2], a feature that may well explain part of the reluctance of the public. On the other hand national tax policies like the ones described in 1.2, made progressive by an indexation on one or more vehicle characteristics, are successfully implemented in many countries and regions.

In this work we want to investigate progressive national-like vehicle charging policies at the city level. Such a policy may have the ambitious scope of road pricing plans, combined with better

[1]Exemptions are often granted to various categories of very green vehicles. These categories represent a small share of car sales however.

[2]The Ecopass charge in Milan was differentiated based on the emission standard of a vehicle, but this characteristic offers little progressivity (see (8.2)).

public acceptance and broader goals. In particular we want to investigate which vehicle characteristic could best be used to index the charge and make it progressive. It is not sure that the vehicle characteristics used at the national or supranational levels to achieve certain goals are the ones best fitted for cities with possibly different objectives. Before bringing the analysis forward, we want to shed light on car characteristics that are serious candidates for the progressive design of a charging scheme at the city level, although they are less visible in current discussions than CO_2 emissions or fuel economy.

3.2 Physical definition of sufficiency and efficiency

In this part we illustrate how *efficiency* and *sufficiency* are two distinct concepts of particular relevance when discussing the consumption of vehicles. As formulas are here mainly explanatory and not used to carry out rocket-science calculations, a simple physical model is used, assuming the following:

- heating and air conditioning are turned off,
- roads are flat,
- the efficiency of the powertrain is constant.

To move, a vehicle using tires has three resistances to overcome (Kasseris 2006):

- the aerodynamic drag,
- the rolling resistance and,
- the inertia, *i.e.* the resistance to a change of motion.

Aerodynamic drag

At any given time t, the aerodynamic force F_a is given by Kasseris 2006:

$$F_a(t) = \frac{1}{2}\,\rho\, S\, C_x\, v(t)^2 \quad [\mathrm{J\,m^{-1}}] \tag{3.1}$$

where

ρ is the air density in $\mathrm{kg\,m^{-3}}$, slightly varying around its average value of $1.3\,\mathrm{kg\,m^{-3}}$,

S is the frontal surface of the vehicle in $\mathrm{m^2}$,

C_x is the dimensionless drag coefficient, characterizing the shape of the vehicle,

v is the speed of the vehicle in $\{m.s^{-1}\}$.

As we can see the air resistance is increasing rapidly with the speed of the vehicle.

Rolling resistance

The rolling resistance can be described as follows:

$$F_r(t) = C_r\, m\, g \quad [\mathsf{J\,m^{-1}}] \tag{3.2}$$

where

C_r is the dimensionless friction coefficient, on average 10^{-2} *i.e.* $10\,\mathrm{kg/t}$ in Europe (Fontaras and Samaras 2010),

m is the mass of the vehicle in kg, on average $1350\,\mathrm{kg}$ for European cars (Fontaras and Samaras 2010),

g is the acceleration of the gravitational field, $g = 9.8\,\mathrm{m\,s^{-2}}$.

In the first approximation described by this formula, the rolling resistance does not depend on the speed of the vehicle, and is thus constant over the trip.

Inertia

Inertia is simply the mass times the acceleration:

$$F_i(t) = m\,\frac{dv}{dt}(t) \quad [\mathsf{J\,m^{-1}}] \tag{3.3}$$

Among those three resistances to motion, the aerodynamic drag is the only one that doesn't depend on the mass of the vehicle. For a discussion of the relative importance of these resistances in different road conditions, see appendix A.1.

Total energy needed and consumption

The total energy needed to overcome these three resistances is proportional to the power developed by the three forces presented above. For each force, the power is obtained by multiplying the force by the current speed of the vehicle. However to estimate the consumption, we don't want to take into account the power developed by the resistance forces when the vehicle is decelerating; in this situation, the power needed to overcome the inertia is mainly delivered by the brakes, and to a lesser extent by the rolling and aerodynamic resistances. We thus obtain the following formulas:

$$P_a(t) = \frac{1}{2}\,\rho\, S\, C_x\, \left(v(t)^3\right)_{acc} \quad [\mathsf{J\,s^{-1}}] \tag{3.4}$$

$$P_r(t) = C_r\, m\, g\, \left(v(t)\right)_{acc} \quad [\mathsf{J\,s^{-1}}] \tag{3.5}$$

$$P_i(t) = m \left(v(t)\, \frac{dv}{dt}(t) \right)_{acc} \quad [\mathsf{J\,s^{-1}}] \tag{3.6}$$

where for any variable x, $x_{acc} = \begin{cases} x & \text{in an acceleration phase} \\ 0 & \text{in a deceleration phase} \end{cases}$

Thus the power needed at the wheel to overcome the three resistances to motion is the sum

$$P_{wheel}(t) = P_a(t) + P_r(t) + P_i(t) \quad [\mathsf{J\,s^{-1}}] \tag{3.7}$$

However before this power can be used at the wheel, it has to be obtained from a primary source, for example fuel in the case of a vehicle with a combustion engine, battery energy in the case of an electric vehicle, *etc.* This conversion is made by the powertrain of the vehicle and occurs with a certain efficiency, known as the powertrain efficiency γ:

$$\gamma(t) = \frac{P_{wheel}(t)}{P_{tank}(t)} < 1 \tag{3.8}$$

where $P_{tank}(t)$ is the power taken from the tank at the time t.

In the case of an electric engine, a typical value value for γ is 0.7, with little variations with time. Thus an electric powertrain converts 70% of the battery energy into energy used at the wheel, and 30% into lost heat. In the case of a combustion engine, the efficiency is much smaller, $\gamma \simeq 0.3$, with stronger variations depending mainly on the temperature of the engine and the engine rotation speed. Here we assume γ is constant: $\gamma(t) = \gamma$.

All in all, the total energy needed E_{tot} over a period of time starting at $t = 0$ and finishing at $t = T$ is obtained by summing the power needed at the tank over time:

$$E_{tot} = \int_0^T P_{tank}(t)\, dt \quad [\mathsf{J}]$$

Following equation (3.8), this energy is the energy needed at the wheel divided by the efficiency of the powertrain:

$$\begin{aligned} E_{tot} &= \int_0^T \frac{1}{\gamma}\, P_{wheel}(t)\, dt \\ \text{i.e. } E_{tot} &= \frac{1}{\underbrace{\gamma}_{efficiency}} \int_0^T \underbrace{E_{wheel}(t)}_{sufficiency} \quad [\mathsf{J}] \end{aligned} \tag{3.9}$$

Finally, the consumption C is simply the total energy needed at the wheel between $t = 0$ and $t = T$ divided by the total distance travelled during this period:

$$C = \frac{E_{tot}}{Total\ distance\ travelled} \tag{3.10}$$

Throughout this work, we refer to the energy needed at the wheel as the *sufficiency*. The less energy a vehicle requires at the wheel for a given motion, the more *sufficient* it is. This decomposition of the final consumption, into sufficiency on the one hand, and efficiency on the other hand, will be used in the subsequent discussion. Indeed, public policies are often directed towards greater efficiency, for example by promoting electric vehicles. Policies involving a greater sufficiency, *i.e.* less energy needed at the wheel, are less often debated.

It is important to stress that sufficiency and efficiency are very distinct concepts. A vehicle is efficient if it converts most of the energy it is given into useful energy, i.e. kinetic energy, energy for the air-conditioning, *etc.* Efficiency is improved through the use of better technologies. However efficiency alone tells nothing about the final consumption of a vehicle. For example a heavy vehicle equiped with modern technologies can have a high consumption despite being efficient, because a lot of energy is needed at the wheel to overcome its inertia.

On the other hand sufficiency is related to three characteristics of a vehicle: its mass (equations 3.2 and 3.3), its friction coefficient (equation 3.2), and its aerodynamism (SC_x, equation 3.1). Among those, weight is the one that impacts sufficiency the most (see appendix A.1). Thus simply put, a vehicle is sufficient if it is light. Again, sufficiency alone tells nothing about final consumption. Old vehicles were often light but inefficient, and thus add high consumption levels.

In the following, we also refer to surface as a sufficiency characteristic. The justification comes from the statistical analysis, where it is shown that weight is closely related to surface. More generally, we refer to characteristics related to the size of a vehicle as sufficiency characteristics.

3.3 Weight and surface in car policies

Although less visible nowadays than CO_2 emissions or fuel economy, vehicles' mass and surface are part of the design of all fuel economy standards around the world, as presented in section 1.2 and table 1.1. Specifically, they are used to obtain an indicator of the "efficiency" of a car fleet (P Mock 2011). In this context the obtained "efficiency" is not strictly equal to the physical definition given in the previous section. Depending on the target and the adjustment factor used, this approximation of the efficiency is:

$$"Efficiency" = \frac{Mass \text{ or } Footprint}{CO_2\ emissions \text{ or } Fuel\ consumption}$$

Compared to the physical definition given by equation 3.9, the total energy E_{tot} is replaced by either fuel consumption or CO_2 emissions. It is justified given that in the case of vehicles with internal combustion engines, fuel consumption is rigorously proportional to E_{tot} (equation 3.10), while CO_2 emissions are closely related to fuel consumption. At the numerator, the wheel energy E_{wheel} is replaced by either mass or footprint. This is very important as:

- Weight appears well-suited to approximate the sufficiency of a vehicle, confirming what can be inferred from equations 3.2 and 3.3 (see appendix A.1).
- Footprint, used as an adjustment factor in Canada, the US and Mexico, also appears as a good approximation of sufficiency.

The use of weight and footprint to adjust fuel economy targets for each car maker suggests that they are key determinants of fuel consumption and CO_2 emissions. However in the context of fuel economy standard, they are not the target of the policy, on the contrary. They are used as adjusting factor so that a fleet of vehicle is evaluated based on its efficiency only, and not on its final consumption or emission level[3]. Simply put, fuel economy standard aim at more efficient cars, regardless of their sufficiency. At the national and supranational levels, the intent is to avoid a distortion of the competition between car-makers and to encourage all of them to improve the environmental performance of their vehicles (P Mock 2011).

Hence, fuel economy standards around the world show that weight and footprint can be used as simple approximations of fuel consumption and CO_2 emissions. They also indicate that large-scale car policies are designed precisely not to target the weight or the size of vehicles, focusing on efficiency to provide incentives for all car-makers and avoid competitive distortions. At the smaller scale of a city however, concerns regarding the competition between car manufacturers may be regarded as less important, while others, like the use of space or the level of pollution, are more acute than at national or supranational levels.

More generally, reducing the mass or the size of vehicles is repeatedly identified as an important mean of reducing the impacts of our car fleets. (François Cuenot 2009) advocates the direct targeting of weight at national levels. He estimates that if the weight of vehicles had remained constant between 1995 and 2005, the average new vehicle sold in Europe would have emitted 143 gCO_2/km in 2005, instead of the 169 gCO_2/km actually observed (see figure 3.1). Furthermore in studies assessing the technological improvements needed to achieve ambitious reductions of car CO_2 emissions in the future, weight and size reductions are often a significant part of the agenda (Bandivadekar 2008).

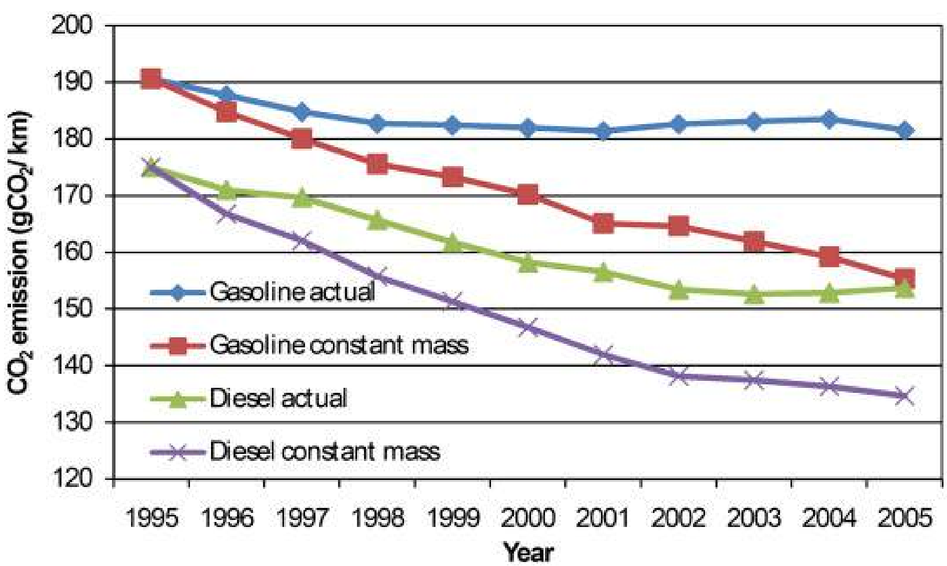

Figure 3.1: Actual CO_2 emissions of European cars and simulated ones if mass had remained constant. Source: (François Cuenot 2009)

One can ask why it is relevant to mention weight or surface when CO_2 emission levels are di-

[3]Which is the result of both the efficiency and the sufficiency of a vehicle.

rectly available for all vehicles and address accurately the problems of pollution. In the literature, some authors refer to economic instruments targeting CO_2 as “first-best” ones to steer low-carbon mobility (Papaix and Meurisse 2013), showing the importance of this vehicle characteristic. Yet as equity issues and public acceptance play an important role when charging cars at the city level, policies based on sufficiency may have advantages over CO_2-based policies: increasing the efficiency of vehicles is generally more costly than downsizing them.

Part II

Methodology

Chapter 4

Construction of the dataset

In this work we use data that we collect to assess the potential of selected car characteristics to serve as indexes for a differentiated car fee in the urban context. In the present chapter we detail the assumptions and procedures we used to gather our dataset, consisting in a collection of cars and their characteristics.

4.1 Assumptions for gathering the data

All cars or only the best sales?

Concerning the models to choose, we decided to focus on the best sales, and this for the following reasons:

- The analysis is not an attempt to build a *predictive* statistical model of the influence of the weight or the surface on consumption. Predictive models already exist, based on statistical or physical analyses. They show the strong influence of the weight on consumption and emissions. But do these correlations hold for the cars actually on the streets?
- The analysis is a way to discuss the potentials of various car fees in an urban context. The correlation factors it produces should not concern all the models present on the market, but the ones (in lower number) that actually represent the majority of cars on the street. As such, we conduct a simpler *descriptive* analysis, to answer questions like: "Given the actual car market, how well is the surface of a vehicle correlated to its CO_2 emissions?"

Thus we conduct a weighted linear regression. The more sales a car has, the more weight is gets in the regression. Again, we don't want to predict the role of weight or surface on different factors, rather we want to describe how well variables are correlated in the actual market.

Which geographical area?

Concerning the geographical area, we decided to focus on Germany as a case example. This choice is motivated by the availability of sales data for the German market (such data are available in most countries however), and simply by the location of the thesis. A more accurate scale to discuss city policies would have benn the city itself. For example, the correlation factors obtained may vary when computed with the cars of Berlin, Munich or Hamburg. However sales data are not available at the city level, and thus we consider the national level as an approximation.

It is worth noting that the German car market is a high-end market when compared to other European markets. In 2013, the average power of new cars sold in Germany was 101 kW, while it was 89 kW in EU-15 countries (CCFA 2014). Cars sold in developing countries may be on average even more different from the ones sold in Germany. If carried in another context, a similar analysis may thus yield different values for the correlation factors. However being mostly due to physical rules, the qualitative conclusions drawn from our study will most likely remain the same. The German case should thus not be considered a restrictive one, but one that illustrates generalizable correlations.

Which version among the many existing ones?

Still there remains an issue regarding which data to choose. In Germany and in most countries, car sales figures are publicly available for diesel and gasoline models, but not for their various versions. Sales number are known for a given model, but this model is most of the time sold in many different versions, with or without start&stop technology, with different levels of equipment, with different forms (sedan, station wagon, spider, etc.), and with different engines. These factors can greatly influence our variables of interest, especially the weight, the emission and consumption levels, and the price.

For a given model, which of these many versions should be chosen to represent the sales of this model? Again, as in our statistical analysis we adopt a descriptive approach to model the car market as it is, the best solution would be to know the sales figure for each version. As these figures are not available, we decided to estimate which version is the most sold for each model, and assign all the sales to this best-selling version.

To estimate which of the many versions is the best-selling one, we used online vehicle marketplaces. On these websites, it is possible to select a specific version of a given model and know how many cars of this version are for sale on the website. It is of course difficult to quantify the accuracy of this method to identify the best-selling version. A good point is that the samples derived from these national websites are large, as for each model many cars are for sale. However it is difficult to know how well do our estimations compare to the actual figures:

- On the one hand we have the unknown sales of each version in 2014.
- On the other hand we have an estimate of these sales derived from an observed proportion of each version. This observation is made in 2015, on a large marketplace, among the used cars first sold in 2014.

What is the accuracy of this estimation? There may be biases if for example used high-end versions are on average put for sale earlier than low-end versions. However there is a priori no reason that such effects affect much the big picture. Moreover for most cars we could observe one of the following scenarios:

- One version neatly dominates the used-car market for a given model, in which case there is little doubt that the actual best-selling version is the estimated one.
- Two similar versions represent the used-car market biggest share. When two versions are dominating the sales for a given model, they most of the time have similar characteristics. In this case the error made by choosing one or the other to represent a model is limited.

The online market places were mainly used to estimate which engines account for the larger sales. Concerning the level of equipment, which primarily impacts the price of a vehicle, we chose to always consider the entry-level version, to avoid the high variability that different sets of options would give to the price of the cars we consider.

Variables gathered

Once a version chosen to stand for a model, all data related to this version were gathered using ADAC's website , where extensive sets of data are available for all cars sold in Germany. The following characteristics were gathered:

- General information:
  - version name,
  - price,
  - body type. This variable has a "Minivan"[1] category gathering typical cars used by families, and a "Bus" category gathering light commercial vehicles.
- Engine:
  - type of charging (turbocharged or not),
  - displacement of the engine,
  - power in PS,
  - start&stop technology (yes or no),
  - propulsion type (2WD or 4WD)
  - transmission type (manual or automatic).
- Sufficiency:
  - length,
  - width,
  - height,
  - weight.
- Performance:
  - acceleration,
  - maximum speed.
- Environmental variables:
  - consumption (urban, extra-urban and overall),

[1] German terminology.

– CO_2 emissions.

On top of these data, two variables were systematically added for each car, namely:

- the surface, computed as $width * length$, as a possible indicator of sufficiency (see 3.3).
- the "inefficiency", computed as $\frac{\mathrm{CO_2}}{\mathrm{weight}}$, included because this metric or similar ones related to efficiency are used to develop emission standards all around the world (3.3). The equivalent "efficiency" ($\frac{\mathrm{weight}}{\mathrm{CO_2}}$) could have been chosen instead. However the two variables bring very similar results in the subsequent statistical analyses, and inefficiency has the advantage that it is a value that is best decreased, as the ones it will be compared to in chapter 7.

Unfortunately, no reliable and comprehensive pollution records could be found.

Let's insist that because each model in the dataset had to be identified to a single version, there is a degree of uncertainty attached to most of these variables. As we systematically chose the most sold engine with the lowest level of equipments, we most likely obtain conservative values regarding performance, CO_2 emissions, consumption, power, and price. It would be worth investigating this error on a few cases where the detailed sales for each version of a model are known, but no such data could be found. Therefore we sometimes refer to the market we study as an "estimated market". However the impact of these inaccuracies is certainly lessened by the fact that in this work we investigate how the characteristics of the cars relate to each other, not what their absolute value is.

4.2 Data wrangling

In this part the procedure that was used to gather the data is described, along with the structure used to store the data.

4.2.1 Sales data

Procedure for gathering the data

For the German car market, sales data are published by the Kraftfahrt-Bundesamt (KBA) on a monthly basis. The data are provided as excel files, one for each month. Each file contains a list of models along with their total (gasoline + diesel) sales for the given month, and their diesel sales. Subtracting the diesel sales from the total sales gives the gasoline sales.

To obtain the sales for the year 2014, the monthly data had to be aggregated. To avoid a tedious aggregation by hand, a program was written in python. It uses the model and car-maker names as keys to correctly match the different models between the 12 excel files.

Sales data obtained

The sales data obtained consist of two datasets, one for gasoline cars and one for diesel cars, each containing the sales data for the top-100 cars sold in Germany in 2014. We calculated that these top-100 make up in both case for more than 90% of the total sales. As an illustration, the sales for the top-10 gasoline cars are presented on figure 4.1.

Figure 4.1: Sales of the top-10 gasoline cars in Germany in 2014.

4.2.2 Vehicle characteristics

As described in section 4.1, once the sales data were obtained for each car model, the most common version was chosen to stand for a given model. Then a set of characteristics was gathered for each of the chosen versions, as listed in 4.1.

Procedure for gathering the data

The ADAC website gives access to a comprehensive database gathering a wide range of characteristics of cars sold in Germany. The procedure that we followed was simple. For each chosen car, the associated webpage is downloaded and saved in a common folder. Then a program is written in python to automatically retrieve and gather the variables of interest. The model and carmaker names are finally used as keys to merge these newly obtained variables with the existing sales data.

Example of the data obtained The dataset is structured as a list of python dictionaries. That is to say, each car is represented by a dictionary, i.e. a set of key-value pairs. As an example, the gasoline version of the Volkswagen Golf is represented as follows in the dataset:


```
[   {   u'acc': 11.9,
        u'adacModel': u'Golf 1.2 TSI BMT',
        u'charging': u'Turbo',
        u'co2': 113,
        u'displ': 1197,
        u'eUrbFE': 4.2,
        u'gasolineSales': 139212.0,
        u'height': 1.452,
        u'hp': 85,
        u'kW': 63,
        u'length': 4.255,
        u'make': u'vw',
        u'model': u'golf',
        u'ovFE': 4.9,
        u'price': 17175,
        u'spd': 179,
        u'startStop': u'Serie',
        u'totalSales': 255044.0,
        u'urbFE': 5.9,
        u'weight': 1205,
        u'width': 1.79}]
```


As we can see, we have a list of key-value pairs corresponding to the sales data, the car-maker and model names, and the variables listed in 4.1. This is how the data is structured. In the next chapter we examine the dataset as a whole and select the variables of interest.

Chapter 5

Main topics investigated and their metrics

To assess the worthiness of various car characteristics as the indexing factors for a differentiated car fee, we list typical topics related to a car policy in an urban context, based on the previous discussion and further literature review. Only topics that are addressable with the data we dispose of are defined in this chapter, along with the statistics we use to analyse them against various vehicle characteristics.

All the metrics presented in this part concern the *potential* of a vehicle characteristic regarding a specific topic, not its actual impact if used to index a progressive car fee. For instance, we assess how well it is possible to target CO_2 emissions by charging based on weight. This however doesn't quantify what would be the impact of a policy effectively charging cars based on their weight, as this impact would depend on the price structure chosen[1].

5.1 Environment and space occupation

Metrics chosen

As shown in the literature review, environment and the use of space are two important topics in many cities, especially in developing countries. The potential of different vehicle characteristics regarding these topics is assessed using Pearson's correlation coefficient r, tailored for continuous variables. For two variables x and y and n observations, r is computed as follows (Washington, Karlaftis, and Mannering 2012):

$$\begin{aligned} r(x,y) &= \frac{\sum(x_i-\bar{x})(y_i-\bar{y})}{\sqrt{\sum(x_i-\bar{x})^2}\sqrt{\sum(y_i-\bar{y})^2}} \\ i.e.\ r(x,y) &= \frac{\operatorname{cov}(x,y)}{\sqrt{\operatorname{var}(x)}\sqrt{\operatorname{var}(y)}} \end{aligned}$$

[1] Possible price structures are discussed in chapter 8.

All the calculations are weighted with the 2014 sales. This coefficient is also the square root of the "goodness of fit" obtained when conducting a linear regression, and often referred to as r^2 in this context.

Why is this metric relevant for our study? Because it quantifies how well it is possible to target a variable through another one, in other words the *potential* of a variable to target another one. If city planners want to target pollution for example, but they don't have a practical way to charge it, they may charge the surface of vehicles instead. If a car's surface is well related to its pollution levels, meaning that for most cars a higher surface is associated with higher pollution levels, charging surface is like charging pollution level, and the initial target is addressed. If on the contrary any level of pollution can be associated with a given surface, charging surface will do little to reduce pollution levels.

The correlation coefficient between two continuous variables A and B should not be confused with the slope obtained when conducting a linear regression on these same variables. The slope can be used to predict B knowing A, but it says nothing about their degree of correlation. For example even if B increases very slowly when A increases, they can be highly correlated. In such a situation, it is still perfectly possible to target B by charging A. On the other hand, if B increases very fast as A increases but the two variables are poorly correlated, A won't be a good vehicle characteristic to target B.

More specifically regarding the environment, we assess how well candidate vehicle characteristic correlates with the CO_2 emissions and urban consumption of the cars present in the dataset[2]. Decreasing CO_2 emissions is an important objective in many cities, and it is nowadays a major metric of green policies. Fuel consumption in the urban context has important impacts on the resilience of a city (in case of higher fuel prices for example) and is closely related to CO_2 emissions. Pollution should definitely have been included to assess the environmental performance of a vehicle characteristic, unfortunately no reliable pollution records could be gathered during this work. Moreover the pollution levels of a car strongly depend on particular technologies, so that it is not clear if CO_2 emissions or urban consumption are robust estimators of pollution levels.

Topic	**Metric used to evaluate vehicle characteristic** $char$
Environment	$r(CO2, char)$, $r(urban\ consumption, char)$
Space occupation	$r(surface, char)$

Table 5.1: Metrics used to assess the potential of candidate car characteristics regarding environment and space occupation

For space occupation, each vehicle characteristic is evaluated based on its correlation with the surface of the cars present in the dataset. The surface of a car is important in an urban context,

[2] In this case the correlation coefficients obtained relate closely to the notion of economic efficiency used in environmental economics (Suter and Walter 2001), as they show how well a charge would target emissions or consumption.

where public space is a limited and valuable resource. Private cars in a city are idle most of the time, and the space they occupy is not available for other use. Thus decreasing the average size of cars could be an objective of city planners, even if no such policy could be found in the literature.

Visualisation of r with data ellipses

Although the correlation coefficient should not be confused with the slope of a linear regression, it is possible to use linear regression combined with data ellipses to visualise the value of a correlation coefficient (Friendly, Monette, and Fox 2013). An example of such visualisation is given on figure 5.2. On such a graph, r is estimated as follows (figure 5.1 gives an illustration):

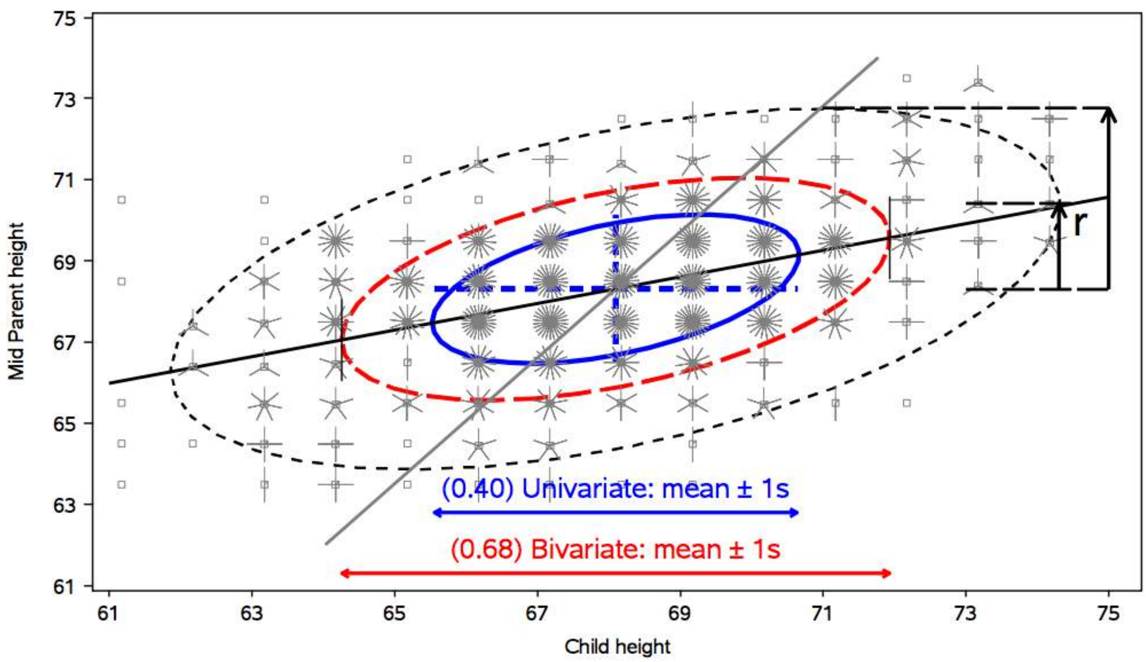

Figure 5.1: Visualisation of r. Source: (Friendly, Monette, and Fox 2013)

$$r = \frac{\text{Vertical distance between center and top of the ellipse}}{\text{Vertical distance between center of the ellipse and the intersection ellipse} \mid \text{regression line}}$$

Intuitively as the spread of the data points around the regression line increases, the size of the ellipse also increases, leading its top to go further from the intersection point between the ellipse and the regression line. On the contrary if the data points are close to the regression line, the ellipse shrinks and tend to merge with the regression line, with its top getting closer to the intersection point.

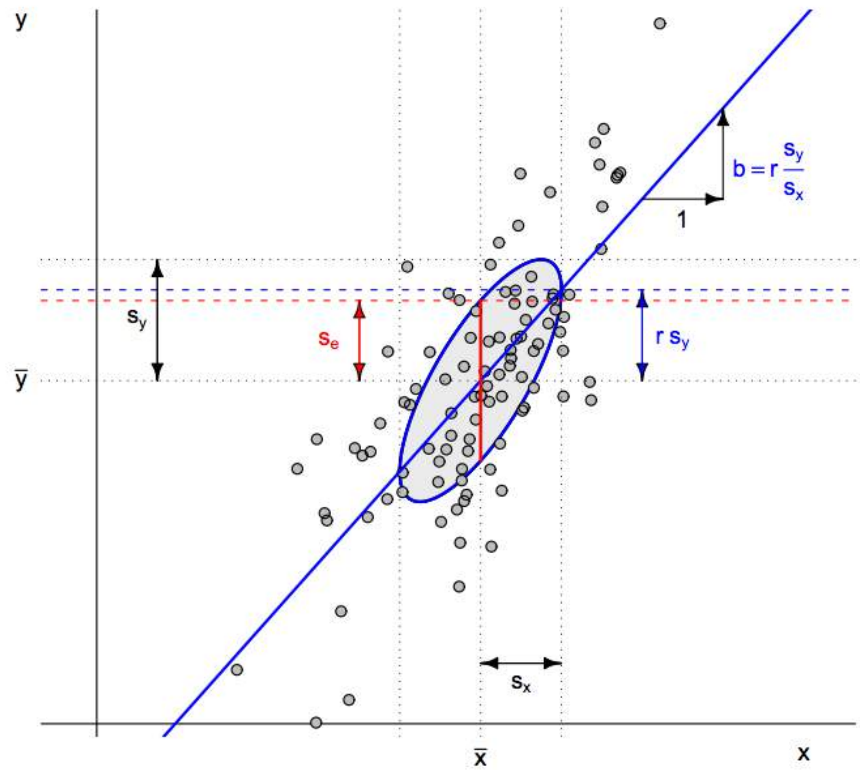

Figure 5.2: Data ellipses can be used to visualise the degree of correlation between two variables. Source: (Friendly, Monette, and Fox 2013)

Limitations

Apart from the particular context of the data (the sales in Germany in 2014), the following factors may have an influence on the results obtained when calculating correlation coefficients:

- Regarding CO_2 and consumption, one source of inaccuracy is the choice of one version to represent all the sales of one model, discussed in 4.1. Another source of inaccuracy comes from the way emissions and consumption are measured. It is estimated that for fuel consumptions and CO_2 emissions, the discrepancy between real world levels and the ones measured using the official procedure defined by the European Union[3] is more than 20% in 2011 (Peter Mock 2013). If the discrepancy was constant for all vehicles, it would have no impact on the correlation coefficients. However it has been reported as showing significant variations between vehicles.
- Regarding surface, the value obtained by multiplying the width by the length of the vehicle is as accurate as the width and length measurements. However again the choice of one version means for example that combi sales don't appear as one point in the regression, rather they are included in the sales of the equivalent sedan version.
- More generally, the CO_2 emissions analysed are only the ones occurring when using the vehicle.

[3] The NEDC, see appendix A.1 for a brief description.

To accurately assess environmental performance in terms of CO_2 emissions, values resulting from a life-cycle assessment[4] should be used, but these data are not available.

- Similarly, one should question the metric used to assess the use of space. The space occupied by a car in motion primarily depends on its speed, not its actual size. However private cars are parked most of the time, suggesting that the size of the cars present in a city has an impact on the space allocated to parking spaces. If cars get on average smaller, the space occupied by parked cars may be reduced and the newly available space used for other purposes.

5.2 Equity and acceptability

Attempts to define equity and acceptability

As we saw in 2.1, acceptability is identified as a major issue when introducing a charge on cars at the city-level. Thus it is interesting to identify what makes a charge on car acceptable or not. In (Souche, Raux, and Croissant 2012), the authors investigate the way inhabitants of Lyon perceive various traffic restrictions. They show that restrictions of traffic to odd/even license plates and tolls justified by congestions are widely considered unjust by respondents. Tolls justified by pollution are perceived more positively, and participants support reduced-rates for low income users, as well as exemptions for car-pooling. All in all, the authors show that perceived justice play a major role in making an urban car policy acceptable or not.

In (Raux and Souche 2004), the authors take a more systematic approach to the problems of justice, equity and acceptability, that are often loosely defined. They use Rawls theory of justice as a base for their definitions. Justice is considered as equivalent to equity, and equity is defined as comprising 4 components: economic efficiency, spatial equity, horizontal equity and vertical equity. This framework is then applied to an urban toll introduced in Lyon in 1997. In this particular context, the authors define the 4 components of equity as follows:

Economic efficiency A robust pricing of congestion or environmental externalities, taking the classical approach described above.

Spatial equity The right to access jobs and services from any location. This limits price increases brought by a new policy, and transport alternatives should be available when transport prices are significantly increased.

Horizontal equity Also referred as the “the user pays” principle. A scheme will be horizontally equitable for example if it makes polluters pay for the damages they cause, or if consumers pay more for a better service, *e.g.* decreased transport times or increased comfort.

[4] Taking into account the emissions related to the making of the materials, their manufacturing, the extraction of the fuel, *etc.*

Vertical equity This last component addresses the issue of social inequalities. A scheme is vertically equitable is it doesn't decrease and possibly increases the welfare of the most underprivileged in the society, an idea that is also known as the "maximin principle". A policy should never decrease the welfare of the least well-off, on the contrary it should aim at maximising it.

Metrics chosen

Vertical equity

With our data, we can assess economic efficiency and horizontal equity regarding environmental externalities, as already described above. Having no spatial data, we are not able to directly discuss spatial equity issues. Vertical equity is assessed using the following metric:

$$dev_{10\%\,cheapest}(char) = \frac{\mu_{10\%\,cheapest}(char) - \mu(char)}{\sigma(char)} \tag{5.1}$$

where:

$dev_{10\%\,cheapest}(char)$ is the vertical equity index for vehicle characteristic ind.

$\mu_{10\%\,cheapest}(char)$ is the mean value of the vehicle characteristic among the 10% cheapest cars, weighted with the 2014 sales.

$\mu(char)$ is the mean value of the vehicle characteristic among all cars, weighted with the 2014 sales.

$\sigma(char)$ is the standard deviation of the vehicle characteristic among all cars, weighted with the 2014 sales.

The more negative is $dev_{10\%\,cheapest}$, the better is the level of vertical equity. Positive values mean on the contrary that the cheapest cars will on average be charged a higher rate than the average. Dividing by the standard deviation make it possible to compare the values obtained for different vehicle characteristics. As the correlation coefficient is used to assess the *potential* of a vehicle characteristic for environmental efficiency, ve is used to assess the potential of a vehicle characteristic for vertical equity. The level of vertical equity actually achieved will depend on the pricing scheme chosen. If for instance the weight of cars is used as an index to charge cars, vertical equity *can* be achieved if the least well-off have cars that are at the light-end of the spectrum (high ve). However based on the pricing chosen, the actual result for the least well-off may vary:

- In case policy-makers choose to use a linear pricing (the charge increases linearly with the weight), the least well-off will be the ones that have the lowest increase of their car transport cost.
- If it is decided that only half the cars will be charged (the heaviest half), the least-well off will very likely pay nothing.

Equity

More generally, we want to assess the potential of each vehicle characteristic to predict the price of a vehicle. This is an approach similar to vertical equity, except that everybody is considered, not only the least well-off. For this purpose we calculate the correlation coefficient between price and every vehicle characteristic, $r(price, char)$.

Acceptability

Acceptability is certainly not predictable in advance by analysing data. Still we can define and measure factors that are regarded as important for an urban car fee to be accepted. The concern for justice mentioned above suggests that equity and vertical equity impact acceptability. If tolls justified by pollution are better perceived than the ones justified by congestion, it suggests that a charge based on a vehicle characteristic predicting well the consumption and emission levels of a car will have greater acceptance. Moreover we include the potential of a vehicle characteristic to predict surface $r(surface, ind)$ in the assessment of acceptability. Indeed we think that a charge that would have as one objective to foster the use of smaller cars in the city would be better accepted. The metrics we plan to use are summarised in table 5.2.

Topic	**Metric used to evaluate vehicle characteristic** $char$
Vertical equity	$dev_{10\%\,cheapest}(char)$
Equity	$r(price, char)$
Acceptability	Environment + Surface + Vertical equity + Equity

Table 5.2: Metrics used to assess the potential of candidate vehicle characteristics regarding equity and acceptability

Limitations

The vertical equity index ve has the following limitations:

- We assume that the least well-off buy the cheapest cars, so that it is possible to assess the impact of a charge on this group by considering the cheapest cars in the dataset. This is certainly the largest source of uncertainty regarding the accuracy of this metric. Indeed the least well-off in a society will often buy second-hand cars, a market that is not comprised in the dataset we have and where the cheapest cars may not have the same characteristics as the cheapest new cars.

- 10% is an arbitrary value. It would have been possible to take 20%, 5%, *etc.* However for $\mu_{10\%\,cheapest}(char)$ to be significant, this category should comprise a sufficient number of models. 10 models make up for the cheapest decile of the gasoline sales in 2014, 20 models in the case of diesel cars. These models are listed in appendix B.1.
- There is also an approximation given that the analysis is carried only on the cars sold in 2014. However it is reasonable to assume that the patterns that are found for the cheapest cars in 2014 (for example that they are on average lighter) held in the past and will continue to hold.

For all metrics there are also inaccuracies due to the assumptions made to choose one version to represent one model (see 4.1), for example prices are the ones of the entry-level version.

5.3 Families, professionals and industrial neutrality

Metrics chosen

Families and professionals

With the data we gathered it is also possible to assess the impact that each vehicle characteristic would have on particular groups. Here we consider families and professionals, by using the categories present in the ADAC data. The “Minivan” category includes typical family cars. The “Bus” category gathers light commercial vehicles (LCV) used by many professionals. For those two categories, we use the same metric as for vertical equity:

$$dev_{family\,cars}(char) = \frac{\mu_{family\,cars}(char) - \mu(char)}{\sigma(ind)}$$

$$dev_{LCV}(ind) = \frac{\mu_{LCV}(char) - \mu(char)}{\sigma(char)}$$

where:

$dev_{family\,cars}(char)$ is the “family index” for vehicle characteristic $char$,

$\mu_{family\,cars}(char)$ is the mean value of the vehicle characteristic among the “family cars” listed in appendix B.2, weighted with the 2014 sales.

$dev_{LCV}(char)$ is the “professionals index” for vehicle characteristic $char$,

$\mu_{LCV}(char)$ is the mean value of the vehicle characteristic among the light commercial vehicles listed in appendix B.3, weighted with the 2014 sales.

A vehicle characteristic $char$ won’t put a particular burden on families if its family index is close to 0. If it is positive, families will be charged more than average, and if it is negative, they will be charged less. The same applies for professionals.

Industrial neutrality As we have seen in 1.2, car policies designed at the national and supranational levels put a strong emphasis on industrial neutrality. Emission targets are calculated for each manufacturer to avoid a distortion of the competition and to encourage all of them to improve the environmental performance of their vehicles. Although at the city level a stronger emphasis can be put on other factors, such as local pollution and the use of space, we assess the potential of each vehicle characteristic to be neutral for car manufacturers. The metric we use measures the variability of each vehicle characteristic among car manufacturers:

$$c_v(char) = \frac{\sqrt{\sum(\mu_m(char) - \mu(char))^2}}{\mu(char)}$$

where:

$c_v(char)$ is the coefficient of variation for vehicle characteristic $char$,

$\mu_m(char)$ is the average value of vehicle characteristic $char$ for the 2014 sales of car manufacturer m,

$\mu(char)$ is the average value of vehicle characteristic $char$ for the 2014 sales.

Due to the division by the mean value of the vehicle characteristic $\mu(char)$, the coefficient of variation c_v is a relative measure of dispersion (Washington, Karlaftis, and Mannering 2012). As such it provides a ground to compare the variability of each vehicle characteristic among car manufacturers. It is important to note that with this metric we don't give more importance to one car manufacturer based on its sales. For example weighted values are used to calculate the average weight of the cars produced by a manufacturer, but then every manufacturer is given the same importance in the calculation of $c_v(char)$. A manufacturer producing few cars will have the same impact on the coefficient of variation as the one with the highest sales. Indeed if the goal of $c_v(char)$ is to measure a potential impact on competition and diversity, dominant competitors should not be given more importance than marginal ones. Table 5.3 summarises the metrics defined in the present section.

Topic	**Metric used to evaluate vehicle characteristic $char$**
Families	$dev_{family\,cars}(char)$
Professionals	$dev_{LCV}(char)$
Industrial neutrality	$c_v(char)$

Table 5.3: Metrics used to assess the potential of candidate vehicle characteristics regarding families, professionals and industrial neutrality

Limitations

The limitations already mentioned related to the way we estimated the German market in 2014 still hold. In particular regarding the equity metrics, the prices of our cars are likely underestimated on average, as only entry-level versions without expensive options were considered. However if this underestimation occurs for all models, the final influence on the correlations or deviations should not be too important. Also, the metric we propose to assess industrial neutrality gives the same weight to all the cars sold by a manufacturer, regardless of their price. However if a reasoning was to be made in terms of sales revenue (and not sales number) of a car-maker, the average value of vehicle characteristic $char$ for manufacturer m, $\mu_m(char)$, should be weighted by sales and price.

Chapter 6

Overview of the dataset and selection of car characteristics

In this chapter we conduct a first analysis of our dataset to select the candidate vehicle characteristics, *i.e.* the car characteristics that could plausibly be used as indexes for a progressive car fee at the city level.

To understand how the variables in a dataset relate to each other, computing the correlations between each variables is a handy first approach. Several correlation coefficients exist to quantify how much two variables are correlated. The Spearman correlation coefficient, applicable to both continuous and ordinal variables, is well-suited for a first analysis of the whole dataset.

Once this analysis is done for gasoline and diesel cars, we list the car characteristics whose potential we want to evaluate.

Spearman correlation coefficient

The Spearman correlation coefficient r_S measures monotonic relations between two variables. It is not computed based on the actual values taken by the variables, but on the ranks of these values. For two variables x and y and n observations, r_S is computed as follows (Washington, Karlaftis, and Mannering 2012):

$$r_S = 1 - \frac{6 \sum_{i=1}^{n} d_i^2}{n(n^2-1)}$$

with

$d_i = \mathrm{rank}(x_i) - \mathrm{rank}(y_i)$ the difference between the ranks of the considered observations.

r_S equals 1 in case it measures “perfect” positive correlation, -1 in case it measures “perfect” negative correlation, and 0 when it measures no correlation. Using a computer, computing correlation coefficients for each pair of variables, and thus building correlation matrices, is a straightforward task. However these matrices are difficult to interpret. All the correlation coefficients are there, but the human brain is limited in its capacity to find patterns out of a large amount of numbers. Principal Component Analysis (PCA), coupled with visualization methods, helps identifying such patterns (Friendly 2002):

- PCA is used to reorder the variables based on their "similarity”.
- Colored numbers and varying transparency are used to better visualize the strength of the correlation coefficients.

Variables analysed

Following these principles, correlation matrices are computed for the following variables:

- *price*, the price of the vehicle in euros, a continuous variable.
- *charging*, a binary variable, 0 stands for no charging, 1 for a turbocharged engine.
- *hp*, the power of the engine in horse power, a continuous variable.
- *startStop*, a binary variable, 0 stands for no start&stop technology, 1 for start&stop technology.
- *WD*, a binary variable, 0 stands for 2WD, 1 for 4WD.
- *trans*, the transmission type, a binary variable, 0 stands for manual transmission, 1 for automatic.
- *width*, the width of the vehicle, a continuous variable.
- *surface*, a continuous variable obtained by multiplying the width by the length of the vehicle.
- *weight*, the weight of the vehicle, a continuous variable.
- *acc*, the time needed for the vehicle to accelerate from 0 to $100\mathrm{km/h}$, a continuous variable.
- *spd*, the maximum speed of the vehicle, a continuous variable.
- *urbFE*, the urban fuel consumption in $\mathrm{L}/100\mathrm{km}$, a continuous variable.
- *ovFE*, the overall fuel consumption in $\mathrm{L}/100\mathrm{km}$, a continuous variable.
- *CO2*, the CO_2 emissions in $\mathrm{gCO2/km}$, a continuous variable.
- *inefficiency*, the CO_2 emissions for every $100\mathrm{kg}$, in $\mathrm{gCO2/km/100kg}$, a continuous variable.

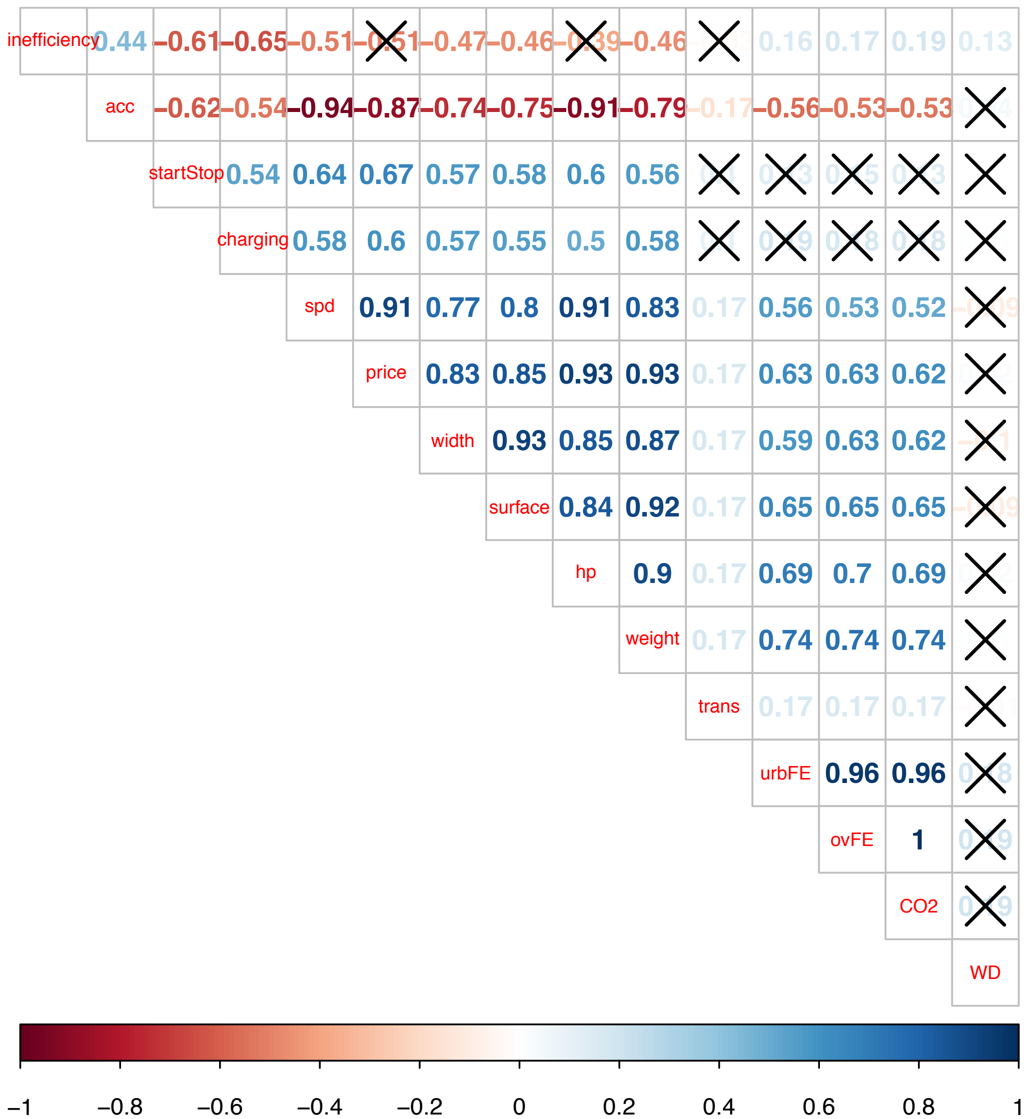

Figure 6.1: Correlation matrix for gasoline cars. Unsignificant coefficients (95% confidence interval) are crossed.

6.1 Results for gasoline cars

The results obtained for gasoline cars are displayed on figure 6.1. We see in particular the following patterns appearing:

- One cluster made of:
  - *acc*,
  - *startStop*,
  - *charging*,
  - *spd*,
  - *price*,
  - *width*,
  - *surface*,
  - *hp*,
  - *weight*.

  This cluster gathers variables related to the size, power, price and performance of the vehicle. We observe very strong positive correlations (above 0.8) between maximum speed, price, surface, weight and power. Acceleration is also very strongly related to these variables, but negatively, as higher performance means less time to accelerate from 0 to $100\text{km}/\text{h}$. There are also strong correlations (0.5 and above) between the latter variables and the categorical variables *startStop* and *charging*. Hence this clusters can be interpreted as indicating what are the usual characteristics of low-end and high-end vehicles: high-end vehicles have a high price, high performance, high weight and surface, turbocharged engines and start&stop technology, and vice versa for low-end vehicles.

- One cluster made of:
  - *urbFE*,
  - *ovFE*,
  - *CO2.*

  This cluster obviously regroups environmental variables. The four variables are very strongly correlated (0.87 and above), which is not surprising given their similarity.

- Between those two clusters, strong positive (negative for the acceleration) correlations can be observed, with values between 0.46 and 0.74. It is interesting to remark that among all the variables analysed, weight is the one that has the strongest correlations to environmental variables, followed by power, surface, width, price, maximum speed and acceleration. The corresponding coefficients are presented in table 6.1. This again suggests that vehicle characteristics related to sufficiency (weight and surface) are promising as a base to develop sustainable mobility policies.

Gasoline	Sufficiency			Performance			Price
	weight	*surface*	*width*	*hp*	*spd*	*acc*	*price*
CO2	0.74	0.65	0.62	0.69	0.52	-0.53	0.62
urbFE	0.74	0.65	0.59	0.69	0.56	-0.56	0.63
ovFE	0.74	0.65	0.63	0.70	0.53	-0.53	0.63

Table 6.1: Sufficiency variables have a good fit to environmental performance.

Gasoline	Sufficiency			Environmental performance			Performance		
	weight	*surface*	*width*	*CO2*	*urbFE*	*ovFE*	*hp*	*spd*	*acc*
price	0.93	0.85	0.83	0.62	0.63	0.63	0.93	0.91	0.87

Table 6.2: Weight and surface have a stronger correlation to price than emission or consumption levels.

- Another interesting point is that the price of a vehicle is more strongly related to weight or surface than to consumption levels or CO_2 emissions, as shown in table 6.2. A possible interpretation is that there are two counteracting effects in the correlation between price and emission levels:

  - on the one hand, more expensive cars tend to be heavier and have higher performances, and thus higher emission levels.
  - on the other hand, it is possible to improve the environmental performance of a vehicle by using expensive technologies and materials.

  The correlation between price and weight or surface is less ambiguous: smaller or lighter cars are mostly less expensive, as shown by the first cluster. This suggests that policies based on sufficiency characteristics may be more equitable[1] than policies based on emission levels. We also remark that power, which is used in some national car taxation schemes, is strongly correlated to price.

- Inefficiency is weakly correlated to environmental variables. It is higher for cars that have better acceleration performance, lower for cars equipped with start&stop technology, and lower for turbocharged engines. Bigger and heavier cars have on average better efficiencies, possibly because they use better technologies.

- The transmission variable is equally correlated to the two main clusters: cars with an automatic transmission tend to have lower environmental performance and are more likely to be high-end vehicles.

[1] In the sense defined in 5.2.

- Finally it appears that a few coefficients are not significant with a 95% confidence interval. Generally speaking, this can be due to the fact that categorical variables provide an information that is less precise than continuous variables. More specifically we can give the following interpretations:
  - Among the 100 gasoline cars of the dataset, only one is a 4WD, which also explains that coefficients related to the propulsion type are mostly not significant.
  - Start&stop technology is not significantly correlated to environmental performance. This may be due to the fact that although this technology improves the environmental performance of a vehicle, it is mostly present on high-end vehicles that have higher consumption and emission levels on average.
  - Turbocharging is not significantly correlated to environmental performance, and an interpretation similar to the one made for the start&stop technology can be made.

6.2 Results for diesel cars

The same variables are analyzed in the case of the diesel cars, except for *charging* which is not included, as all diesel cars of the dataset are turbocharged. Hence 14 variables are used in the correlation matrix, which is presented on figure 6.2. The patterns are similar to the ones observed for gasoline cars:

- Environmental variables (*urbFE*, *ovFE* and *CO2*) form a clear cluster with strong positive correlations.
- The cluster that we interpreted in the case of gasoline cars as representing the “class” of a vehicle (low-end or high-end) is still observable, although with a few differences:
  - Turbocharged engines, present on all cars of the dataset, is no more a characteristic of high-end vehicles.
  - Propulsion on the contrary is more correlated to the class of a diesel vehicle: high-end diesel vehicles tend to have a 4-wheel drive.
  - Power, price, surface and weight are very strongly correlated (correlation coefficient is 0.73 or more), as in the case of gasoline cars.
  - Speed and acceleration relate differently to the size of a vehicle and its environmental performance. This is illustrated by the coefficients presented in table 6.3. Bigger diesel cars have on average higher performances than smaller ones, however this positive correlations is much weaker than in the case of gasoline cars. A possible interpretation is that contrary to the gasoline dataset, the diesel dataset contains many light commercial vehicles. Besides for diesel cars performance is weakly related to environmental performance, with correlations that are even insignificant between speed and environmental performance.
- As in the case of gasoline cars environmental performance is strongly correlated to power, price, surface and weight, with coefficients between 0.54 and 0.86. This time the strongest correlation

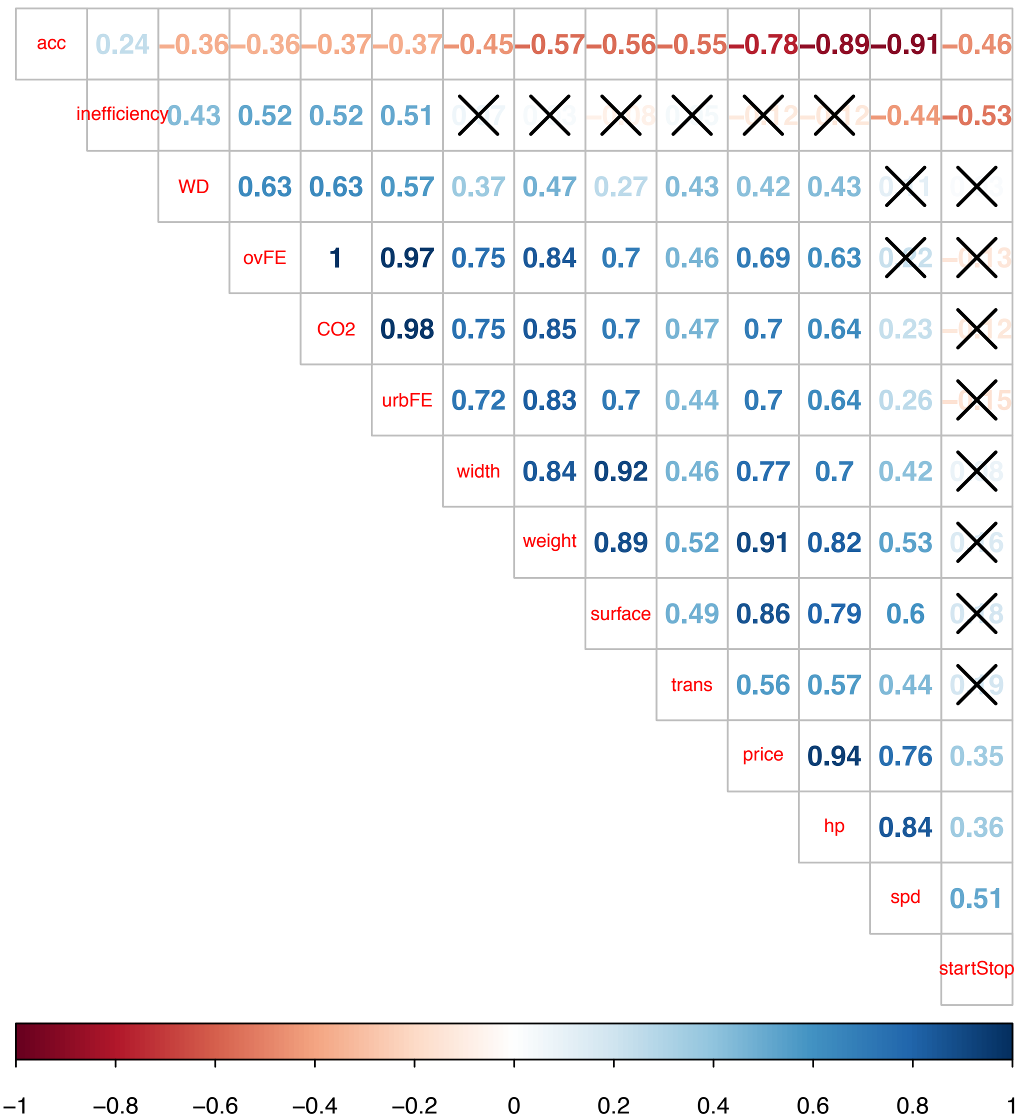

Figure 6.2: Correlation matrix for diesel cars. Unsignificant coefficients (95% confidence interval) are crossed.

Gasoline	*surface*	*weight*	*CO2*	*urbFE*	*ovFE*
hp	0.84	0.90	0.69	0.69	0.70
spd	0.80	0.83	0.52	0.56	0.53
acc	0.75	0.79	0.53	0.56	0.53
Diesel	*surface*	*weight*	*CO2*	*urbFE*	*ovFE*
hp	0.74	0.78	0.59	0.59	0.58
spd	0.47	0.45	0.14	0.17	0.13
acc	0.56	0.57	0.37	0.37	0.36

Table 6.3: Speed and acceleration are much less correlated to environmental performance in the case of diesel vehicles.

is observed for the weight, followed by the width and the surface, and then the price (table 6.4). A vehicle's power appears much less correlated to environmental performance in the case of diesel cars. Again this suggests that weight and surface are characteristics well-suited for sustainable mobility policies, both for diesel and gasoline cars.

Diesel	Sufficiency			Performance			Price
	weight	*surface*	*width*	*hp*	*spd*	*acc*	*price*
CO2	0.86	0.74	0.77	0.59	0.14	0.37	0.70
urbFE	0.84	0.74	0.75	0.59	0.17	0.37	0.69
ovFE	0.86	0.74	0.78	0.58	0.13	0.36	0.69

Table 6.4: Also for diesel cars, sufficiency variables have a good fit to environmental performance.

- As in the case of gasoline cars, weight, surface and width have better correlations to price than consumption levels or CO_2 emissions, as shown in table 6.5. This suggests again that characteristics related to the sufficiency of a car may make it easier to develop acceptable car policies.

- Inefficiency correlates better with environmental performance in the case of diesel cars: inefficient diesel cars consume and emit on average more. It is no more significantly correlated to the size or the weight of a vehicle. It is still correlated with performance: diesel vehicles with better performance have on average lower efficiencies. As in the case of gasoline cars, diesels with start&stop technologies are on average more efficient.

Diesel	Sufficiency			Environmental performance			Performance		
	weight	*surface*	width	*CO2*	*urbFE*	*ovFE*	*hp*	*spd*	*acc*
price	0.90	0.85	0.85	0.69	0.7	0.69	0.93	0.70	0.78

Table 6.5: Weight and surface have a stronger correlation to price than emission or consumption levels.

- Again the transmission variable is positively correlated to many other variables, but this time more strongly: diesel cars with an automatic transmission have on average higher emission and consumption levels and are bigger, heavier, more powerful and more expensive.
- Finally we interpret the non-significant correlations as follows:
  - Start&stop technology is not significantly correlated to environmental performance likely for the same reasons as those given in the case of gasoline cars.
  - The non-significant correlations between speed and environmental performance may be due to the vans and minivans in the diesel dataset, that have low maximum speeds and high emission and consumption levels.

6.3 Insights gained and candidate vehicle characteristics.

Among the interpretations made by analyzing the correlation matrices for diesel and gasoline cars, two are of particular interest with regard to the topics listed in 5:

1. Variables related to sufficiency, namely *weight* and *surface*, are tightly correlated to environmental performance, roughly as much as power in the case of gasoline cars (table 6.1), and even more than power in the case of diesel cars (table 6.4).
2. *weight* and *surface* are also more tightly correlated to the price of a vehicle than other vehicle characteristics that are often used to develop policies, namely the emission or consumption levels. This suggests that charging based on sufficiency may be better accepted than charging based on emission levels (tables 6.2 and 6.5).

The analysis that we conducted has shortcomings however:

- The calculation of the Spearman correlation coefficient r_S is made using the rank of a given variable value ($rank(x_i)$), not its actual value (x_i). Put differently, continuous variables are coerced to ordinal variables, which comes with a loss of information. The Pearson correlation coefficient used in the next chapter is more accurate for continuous variables.
- More importantly, the calculation of the correlation coefficients is not weighted. All cars have the same influence on the coefficients obtained. However as mentioned in 4.1, we want to make a descriptive analysis of the actual cars on the street, so the best sales should weight more

on the computed coefficient than a less successful model. Hence in the next chapter we use sales-weighted calculations to assess the selected vehicle characteristics against the targets defined in chapter 5.

Candidate vehicle characteristics

The existence or not of a particular technology on a vehicle can't be used as a base for a progressive fee. Thus binary variables are not candidate vehicle characteristics. Regarding the continuous variables, we make the following choices:

Performance Acceleration and maximum speed correlate well to the price of a vehicle, but poorly with the environmental performance in the case of diesel cars. Power is tightly correlated to price, and correlates well with environmental performance even for gasoline cars. Thus among the performance characteristics, we choose to include **power** in the candidate vehicle characteristics for a differentiated car fee.

Environmental performance Being very tightly correlated, CO_2 emission and consumption levels have similar correlation coefficients regardless of the other car characteristic considered. To avoid repetitive results we select only **CO_2 emissions** as a candidate vehicle characteristic.

Sufficiency and efficiency The distinction between efficiency and sufficiency being one of the focus of this work, we include **inefficiency** in the subsequent analysis to illustrate its difference from sufficiency. We also include three variables related to sufficiency: the **weight**, the **surface**, and the **width** of a vehicle.

We thus have six car characteristics that could be used to index a progressive car fee introduced in an urban context. In the next part we assess the potential of these six vehicle characteristics regarding the topics we defined in chapter 5.

Part III

Potentials of various car characteristics for indexing large-scale car fees in an urban context

Chapter 7

Insights gained from the data

In this chapter we present the results obtained for all the metrics defined in chapter 5, and we conclude regarding the potentials of the vehicle characteristics selected in the previous chapter.

7.1 Environment and space occupation

Environment

Figure 7.1 gives a visual representation of the potential of the six candidate vehicle characteristics to target CO_2 emissions. Each figure includes a data ellipse, whose form helps to visualise the value of the correlation coefficient, as presented in 5.1. The results concern gasoline vehicles, the corresponding figures for diesel vehicles can be found in appendix C.1 and table (7.1). Looking at these results, we notice that:

- Apart from CO_2 itself, weight is the best predictor of the level of CO_2 emissions, with high correlation coefficients both for diesel and gasoline cars.
- Power is a good predictor of the level of CO_2 emissions for gasoline cars, but it performs poorly for diesel cars. For some reason the emission levels of diesel cars are not so related to the power of their engine.
- Efficiency is well related to the level of CO_2 emissions for diesel cars, but not well for gasoline cars.
- The other variables related to sufficiency (width and surface) are good predictors of the level of CO_2 emissions for diesel and gasoline cars, but not as good as weight.

Space occupation

Figure 7.2 shows the potential of the six candidate vehicle characteristics to target the surface of vehicles, whose reduction we defined as an important objective in an urban context. The results

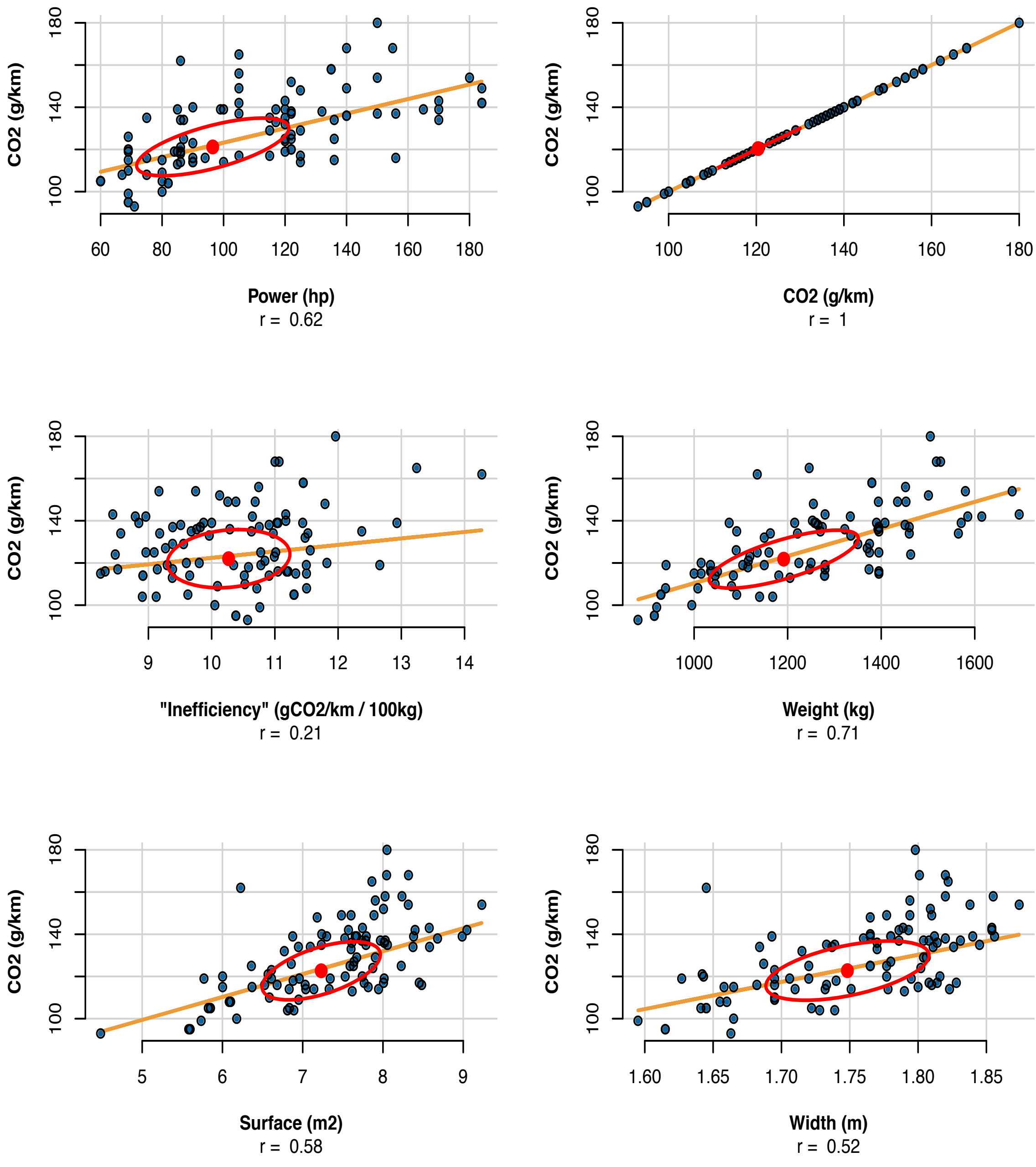

Figure 7.1: Potential of the vehicle characteristics for targeting $\mathbf{CO_2}$ emissions - Gasoline cars

presented on this figure concern gasoline vehicles, the corresponding figures for diesel vehicles can be found in appendix C.1 and table (7.1). We observe in particular that:

- Three vehicle characteristics are very well correlated ($r > 0.8$) to the surface of a vehicle: the surface of course, and the two other vehicle characteristics related to sufficiency, weight and width.
- Power is very well correlated to surface in the case of gasoline cars, a bit less in the case of diesel cars. One possible explanation is that light commercial vehicles are present in the diesel dataset, and they generally have high surface with relatively low power.
- Inefficiency is negatively related to surface, meaning that on average the bigger a car, the more efficient it is. Indexing a charge on the level of efficiency (the more efficient, the less you pay) of a vehicle would favour larger vehicles. Hence efficiency is clearly not an adapted vehicle characteristic for a policy that would aim at favouring the use of smaller cars.
- The level of CO_2 emissions relate positively to the surface of a vehicle, with a satisfying degree of correlation.

Summary

Gasoline	Power	CO_2	Inefficiency	Weight	Surface	Width
$r(CO2, char)$	0.61	1	0.21	0.71	0.58	0.52
$r(urbFE, char)$	0.63	0.97	0.21	0.69	0.55	0.48
$r(surface, char)$	0.80	0.58	-0.56	0.90	1	0.92

Diesel	Power	CO_2	Inefficiency	Weight	Surface	Width
$r(CO2, char)$	0.44	1	0.64	0.83	0.59	0.70
$r(urbFE, char)$	0.41	0.98	0.66	0.79	0.59	0.66
$r(surface, char)$	0.66	0.59	-0.16	0.83	0.76	0.73

Table 7.1: Correlation coefficients obtained for each vehicle characteristic

The coefficients obtained are gathered in table 7.1. This table also contains the correlations for urban consumption, that are very similar to the ones obtained for CO_2. To make these numbers more visible, we use the following color code:

$\mathbf{r(x, y)}$	$< \mathbf{0.2}$	$\mathbf{0.4} < < \mathbf{0.2}$	$\mathbf{0.4} < < \mathbf{0.6}$	$\mathbf{0.6} < < \mathbf{0.8}$	$\mathbf{0.8} < < \mathbf{1}$
COLOR CODE	--	-	o	+	++

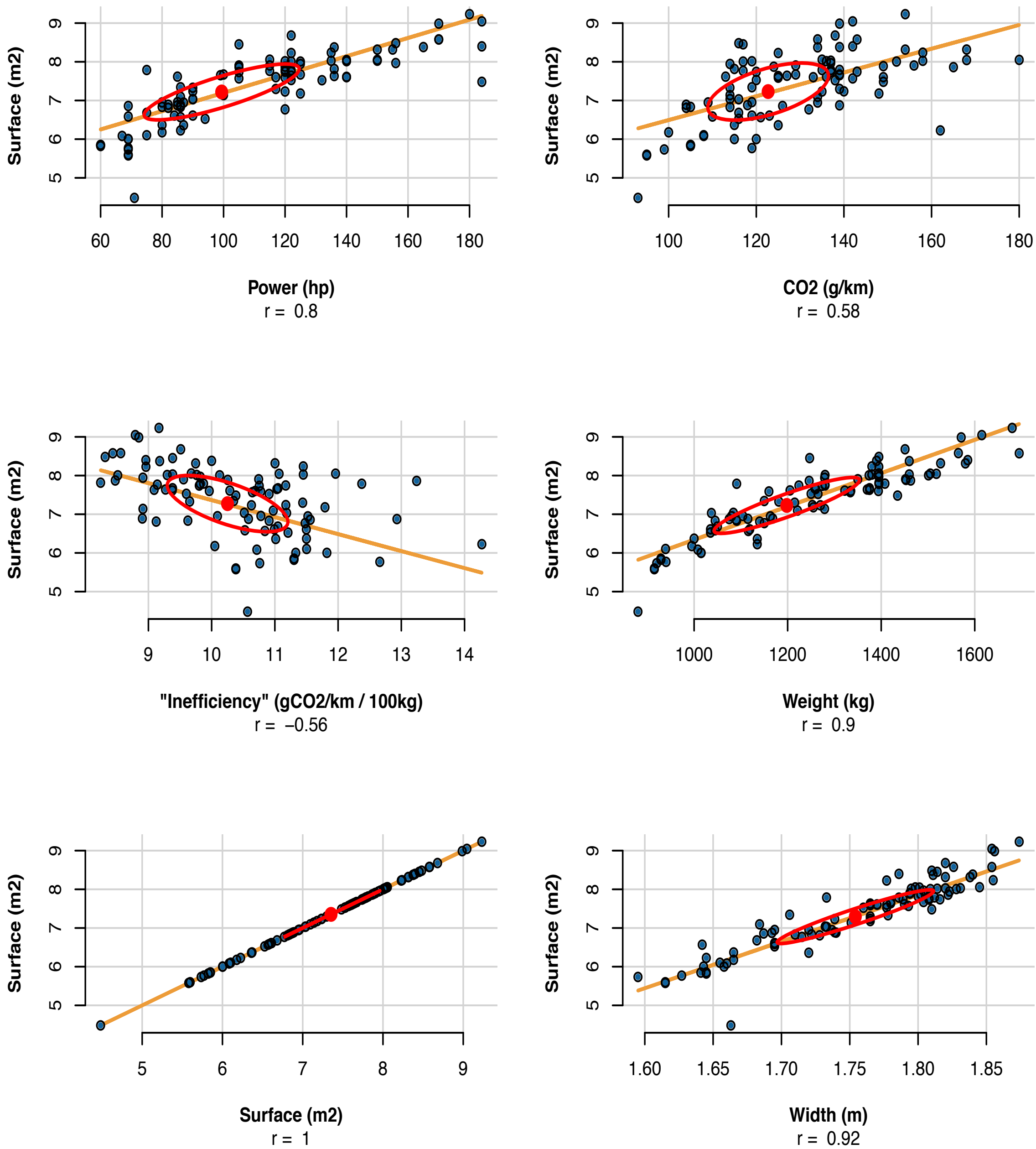

Figure 7.2: Potential of the vehicle characteristics for targeting **surface** - Gasoline cars

This color code is used to visually present how well a vehicle characteristic is suited regarding a given topic. It is not directly applied to each correlation coefficient presented in table 7.1. Rather, these coefficients are aggregated in a certain way depending on the topic, and then a color code is applied to the aggregated result. Regarding the environment we aggregate the coefficients as follows:

$$\frac{1}{2}(r_{gas+dies}(CO2, char) + r_{gas+dies}(urbFE, char))$$

where:

$r_{gas+dies} = \frac{1}{2}(r_{gas} + r_{dies})$: we give the same weight to diesel and gasoline cars, because they each account for half of the total sales on the German market in 2014.

Regarding the environment we give the same importance to CO_2 emissions and urban consumption. Other choices could be made when assessing a policy, for example if it is decided that CO_2 emissions are more important than urban consumption. However in this case as $r(CO2, char)$ and $r(urbFE, char)$ are very similar for all vehicle characteristics, it wouldn't make a big difference on the final result. Regarding the use of space we simply aggregate the coefficients obtained for diesel and gasoline cars:

$$r_{gas+dies}(surface, char)$$

The resulting potentials of each vehicle characteristic regarding the environment and the use of space are presented in table 7.2. Inefficiency is a bad vehicle characteristic regarding the use of space in the sense that charging inefficiency would foster the use of larger vehicles. For a city that would aim at having low-emission vehicles but also smaller ones, weight is the most versatile vehicle characteristic.

	Power	**CO_2**	**Inefficiency**	**Weight**	**Surface**	**Width**
ENVIRONMENT	o	++	o	+	o	o
SPACE OCCUPATION	+	o	– –	++	++	++

Table 7.2: CO_2 appears as the best vehicle characteristic regarding the environment, and weight as the best to favour vehicles that are both green and small

7.2 Equity and acceptability

Vertical equity

Figures C.3 and C.4 give a visual representation of the vertical equity metric presented in equation 5.1, for CO_2 emissions and power (figure C.3), and weight and inefficiency (figure C.4). The results for width and surface are similar to the ones obtained for weight and thus not visualised. On each axis, the gray line represents the mean value of the vehicle characteristic among all cars, the blue one represents the mean value among the cheapest decile, and the orange line is one standard deviation away from the overall mean (gray line). Thus the ratio "distance between blue

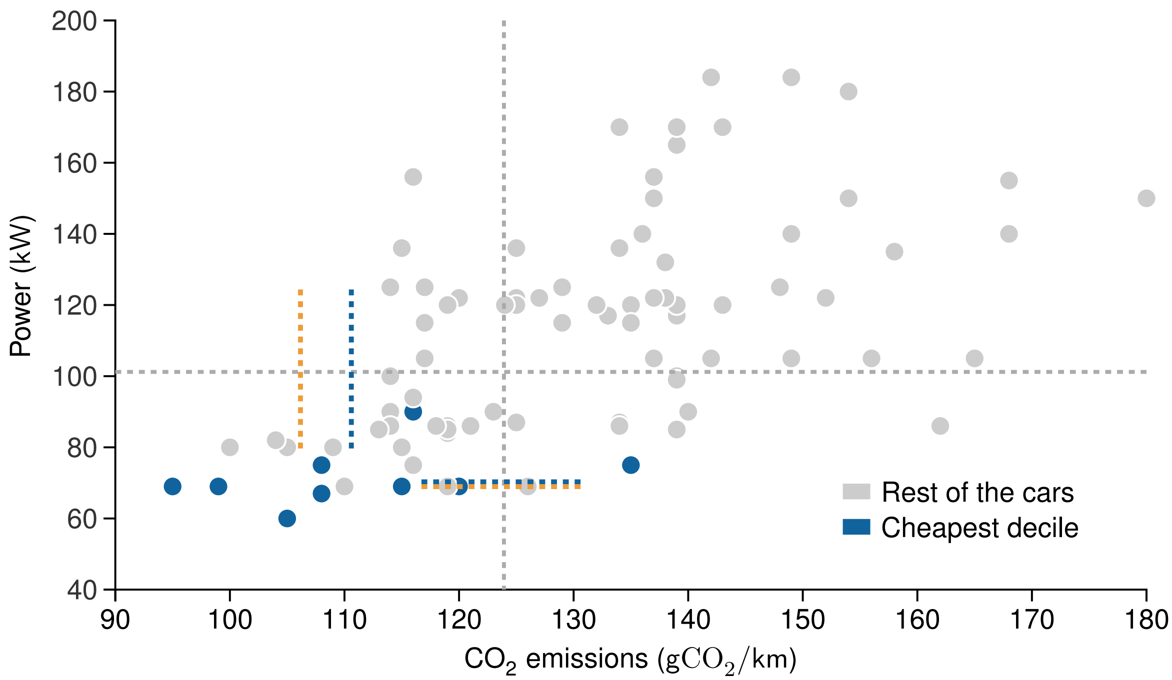

Figure 7.3: The cheapest gasoline cars have low average emissions, and even lower average power.
Gray line: $\mu(char)$. Blue line: $\mu_{10\%\,cheapest}(char)$. Orange line: $\sigma(char)$.

and gray line" over "distance between orange and gray line" is exactly $dev_{10\%\,cheapest}$. Here we chose to present the values obtained for gasoline vehicles, as the cheapest gasolines are much cheaper than the cheapest diesels (see appendix B.1). The corresponding figures for diesel vehicles can be found in appendix C.2. Looking at these figures and at the results gathered in table 7.3, we observe the following for the cheapest gasoline and diesel cars:

- They have low average CO_2 emissions, a bit less than one standard deviation away from the overall average.
- They have low average power, one standard deviation away from the overall average.
- They have low weight, width and surface, a bit more than one standard deviation away from the overall averages.

The results are thus similar for diesel and gasoline cars, except in the case of inefficiency: cheap gasoline cars are much more inefficient than the average gasoline car, while cheap diesel cars are not particularly inefficient. Regardless of the interpretation, inefficiency appears again as inappropriate regarding vertical equity, as indexing a car fee on inefficiency would result in the cheapest cars being more charged than the average.

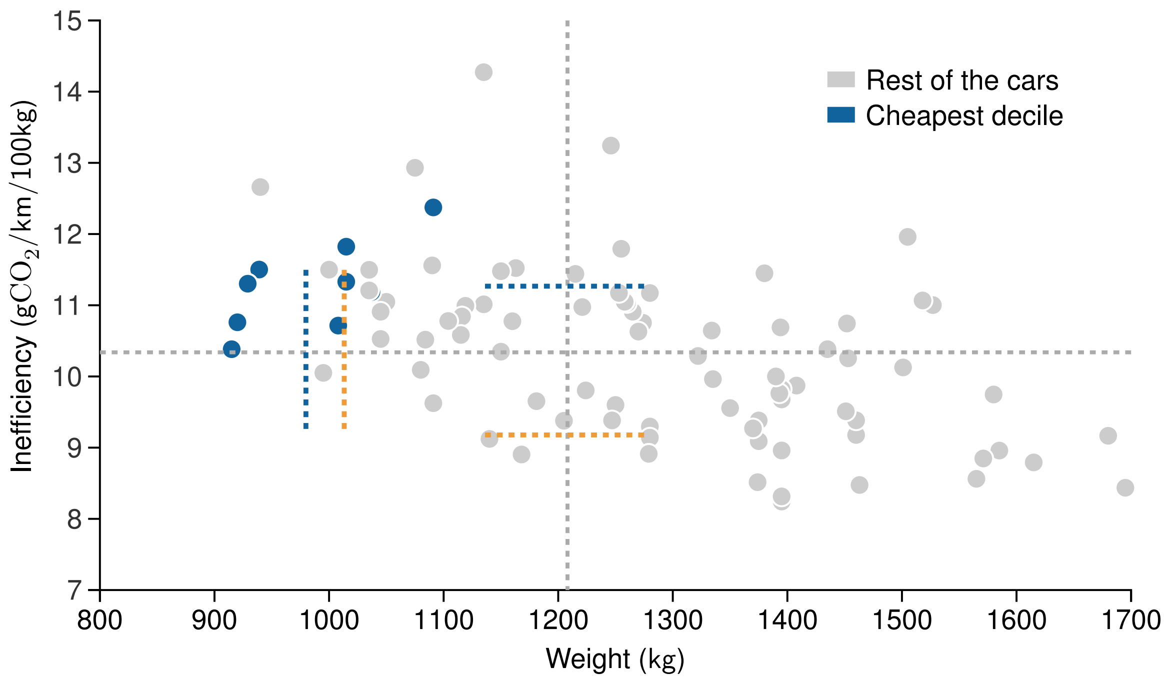

Figure 7.4: The cheapest gasoline cars have very low average weight and high inefficiency. Gray line: $\mu(char)$. Blue line: $\mu_{10\%\,cheapest}(char)$. Orange line: $\sigma(char)$.

Equity

Figure 7.5 helps visualise $r(price, char)$ for each vehicle characteristic, *i.e.* the potential to target the price of vehicles, that we defined as a metric for equity. The results presented on this figure concern gasoline vehicles, the corresponding figure for diesel vehicles can be found in appendix C.2. We observe in particular that:

- Power and weight are both very well correlated to price, with r around 0.9.
- Width and surface are well correlated to price, with r around 0.75.
- As already noted in chapter 6, CO_2 emissions are not so well related to price ($r \simeq 0.5$). On figure 7.5 we can notice that while on average more expensive cars have higher emissions, outlier points show cheap cars with high emission levels, and expensive cars with low emission levels. A possible interpretation is the one already given in 6, that there are two counteracting effects in the correlation between price and emission levels:
  - on the one hand, more expensive cars tend to be heavier and have higher performances, and thus higher emission levels.
  - on the other hand, it is possible to improve the environmental performance of a vehicle by using expensive technologies and materials.
- Price is negatively related to efficiency, making this vehicle characteristic inappropriate regarding equity.

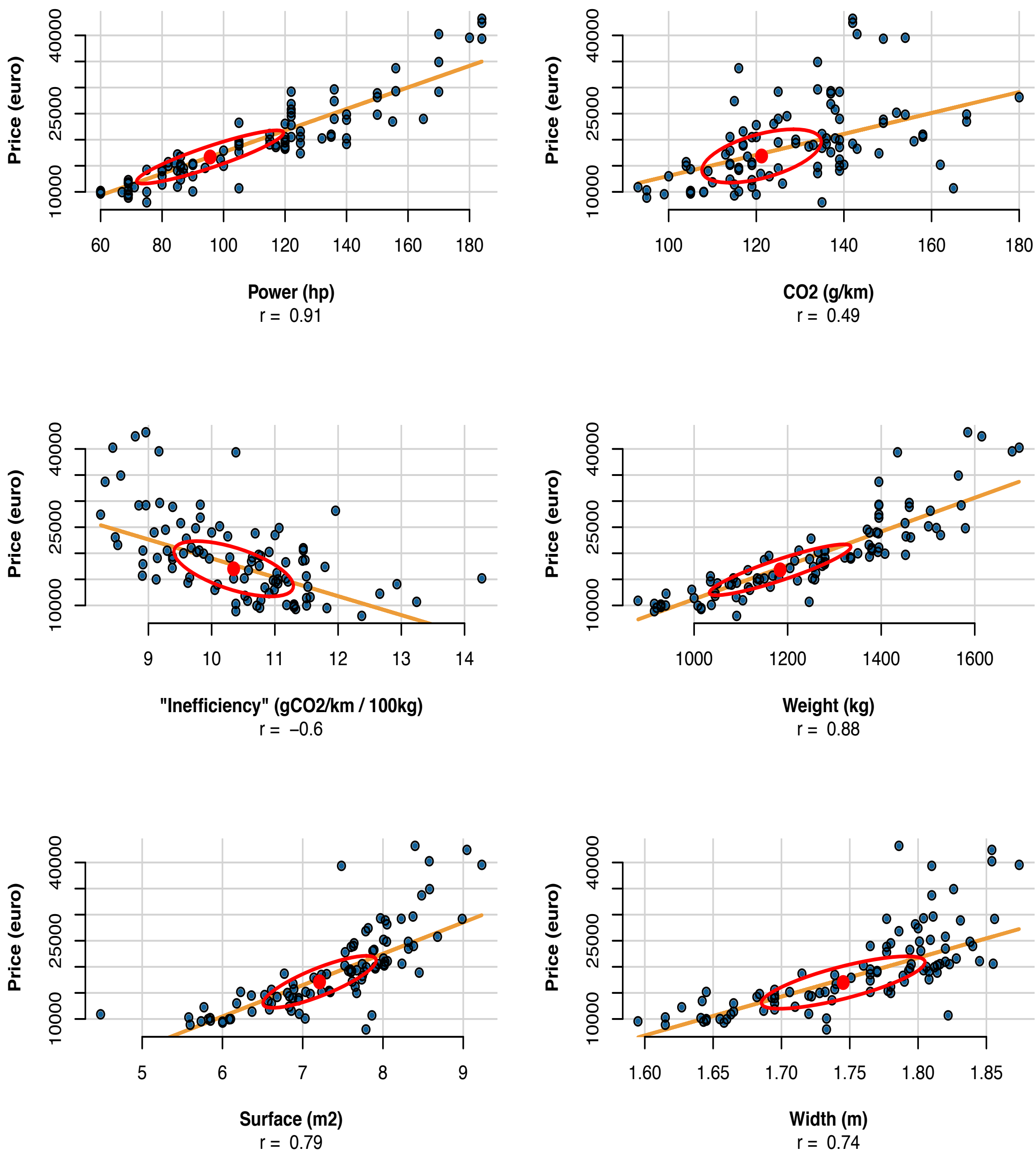

Figure 7.5: Potential of the vehicle characteristics for targeting **price** - Gasoline cars

Summary and acceptability

Gasoline	Power	CO_2	Inefficiency	Weight	Surface	Width
$dev_{10\%\,cheapest}$	-0.9	-0.7	0.8	-1.1	-1.1	-1.3
$r(price, char)$	0.91	0.49	-0.61	0.88	0.79	0.74

Diesel	Power	CO_2	Inefficiency	Weight	Surface	Width
$dev_{10\%\,cheapest}$	-1.0	-0.8	0.2	-1.1	-1.2	-1.1
$r(price, char)$	0.93	0.55	-0.16	0.83	0.76	0.73

Table 7.3: Equity metrics obtained for each vehicle characteristic

The coefficients obtained regarding equity and vertical equity are gathered in table 7.3. For equity (assessed with $r(price, ind)$), we use the color code already presented in 5.1 for other correlation coefficients. For vertical equity we use the following color code:

$\mathbf{dev_{10\%\,cheapest}}$	< -1.2	$-0.8 < < -1.2$	$-0.8 < < -0.4$	$-0.4 < < 0$	$0 <$
COLOR CODE	++	+	o	-	--

This color code is used because $\mathbf{dev_{10\%\,cheapest}}$ should be as negative as possible, meaning that the cheapest cars are well below the average for a given vehicle characteristic, and thus that they would be charged less if this vehicle characteristic was used for indexing a fee. Regarding the aggregation of the coefficients obtained we simply use $r_{gas+dies}(price, ind)$ for equity and $dev_{10\%\,cheapest,\,gas+dies}$ for vertical equity (same importance given to diesel and gasoline cars).

As explained in 5.2, we assess acceptability by aggregating the results obtained for the environment, the use of space, equity and vertical equity. We took the simple approach of assigning a weight of one to each of this topic. Thus, equity metrics (equity and vertical equity) account for half of the weight, how well CO_2 is targeted for a quarter, and how well surface is targeted for a quarter. Again another approach may be taken depending on the political context, but we chose these weights thinking that equity is the prevalent factor for acceptance, while announcing that a policy aims at having greener and smaller cars in a city would also ease acceptance. The resulting potentials of each vehicle characteristic regarding equity and acceptability are presented in table 7.4.

From these results we draw three main conclusions regarding equity and acceptability:

- efficiency if used as an index for a car fee would result in an inequitable policy (in the sense defined in 5.2), with cheaper cars being charged more, and low acceptability. This confirms that the distinction between sufficiency and efficiency is particularly relevant when it comes to equity and acceptability.

	Power	CO_2	Inefficiency	Weight	Surface	Width
VERTICAL EQUITY	+	o	– –	+	+	+
EQUITY	++	o	– –	++	+	+
ACCEPTABILITY	+	o	– –	++	+	+

Table 7.4: Power and characteristics related to sufficiency appear as the best vehicle characteristics regarding equity and acceptability

- CO_2 emissions if used as an index would result in an equitable policy on average, with cheaper cars being charged less. However as some cheap cars have high emissions, while expensive cars sometimes have very low emissions, a number of exceptions to this average equity could exist. All in all, such a policy has a decent potential for acceptability.
- Sufficiency characteristics and power if used as indexes could result in very equitable policies, with a high potential for acceptability.

7.3 Families, professionals and industrial neutrality

Families

Figures 7.6 and 7.7 give a visual representation of the "family index" presented in 5.3, for CO_2 emissions and power (figure 7.6), and weight and inefficiency (figure 7.7). The interpretation of the colored lines is the same as for the vertical equity index, and in this case the ratio "distance between blue and gray line" over "distance between orange and gray line" equals $dev_{family\,cars}$. The values presented are the ones obtained for diesel vehicles, as family cars have mostly diesel engines (see appendix B.2). The corresponding figures for gasoline vehicles can be found in appendix C.3. Looking at these figures and at the results gathered in table 7.5, we make the following observations:

- Diesel family cars have average CO_2 emissions, average efficiency, and average weight, surface and width. They are less powerful than the average diesel car.
- Gasoline family cars differ much more from the average gasoline car. They are heavier, larger, they have higher CO_2 emissions, slightly higher efficiency. As their diesel counterparts, they have relatively low power.

Thus a car fee indexed on power or efficiency could slightly benefit families, while sufficiency or CO_2 indexes would results in neutral to slightly detrimental charges.

Professionals

Figures 7.8 and 7.9 give a visual representation of the "professional index" presented in 5.3, for CO_2 emissions and power (figure 7.8), and weight and inefficiency (figure 7.9). This time the

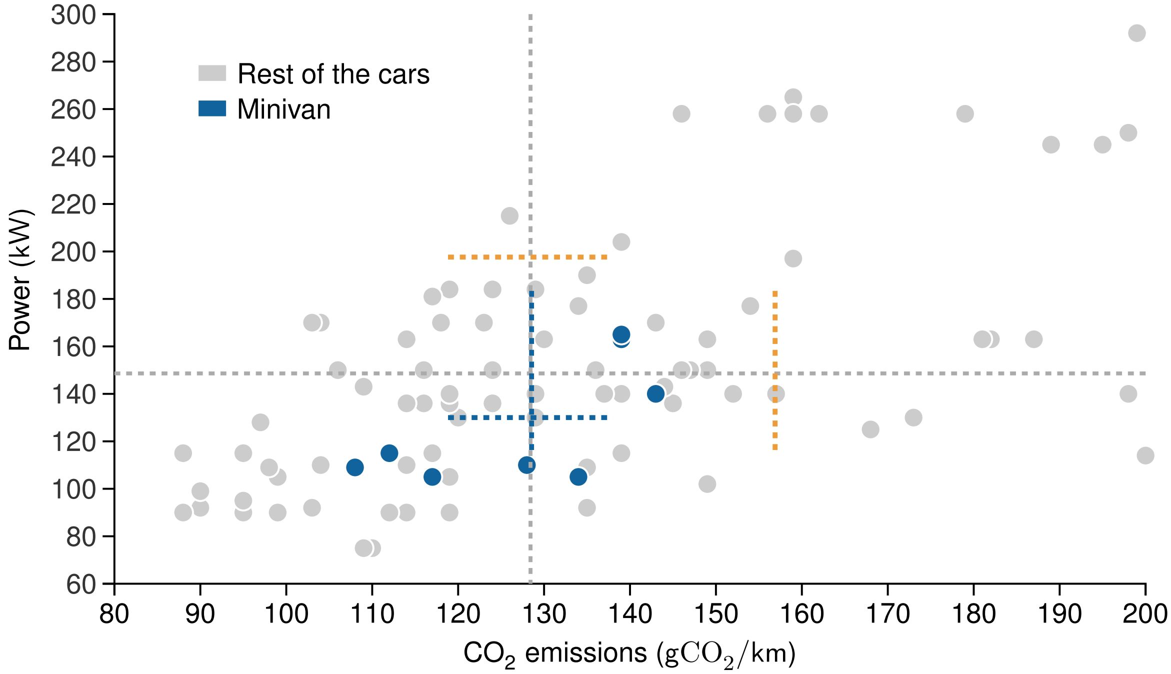

Figure 7.6: Diesel family cars have average CO_2 emissions and lower than average power.
Gray line: $\mu(char)$. Blue line: $\mu_{family\,cars}(char)$. Orange line: $\sigma(char)$.

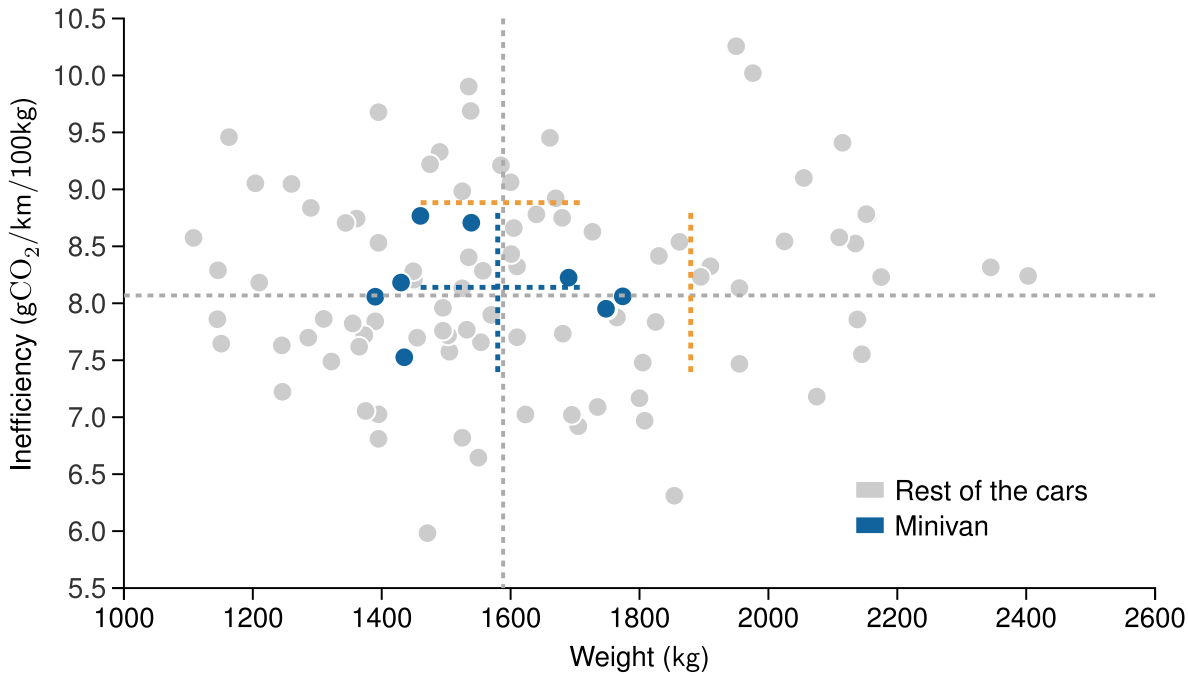

Figure 7.7: Diesel family cars have average inefficiency and weight.
Gray line: $\mu(char)$. Blue line: $\mu_{family\,cars}(char)$. Orange line: $\sigma(char)$.

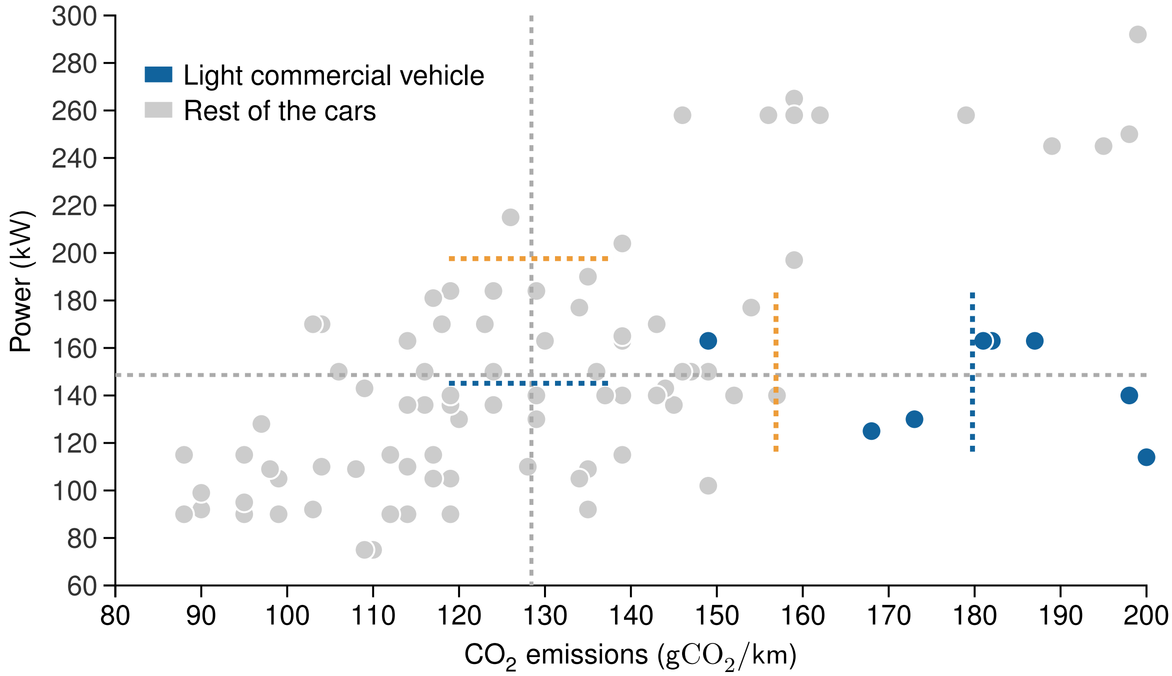

Figure 7.8: Light commercial vehicles have average power and emissions much higher than the average.
Gray line: $\mu(char)$. Blue line: $\mu_{LCV}(char)$. Orange line: $\sigma(char)$.

colored lines represent dev_{LCV} for each vehicle characteristic. The values presented are the ones obtained for diesel vehicles, as all light commercial vehicles have diesel motorisations (see appendix B.3). Looking at these figures and at the results gathered in table 7.5, we make the following observations:

- Light commercial vehicles have very high CO_2 emissions, weight, width and surface.
- They have high inefficiency.
- Only their average power is similar to the average power of the diesel fleet.

Thus among the vehicle characteristics we assess power is the only one that would not put a particular burden on professionals. However if needed a differentiated fee can easily be applied to this well-defined category of vehicles (see 8.3 for a discussion of exemptions).

Industrial neutrality

Figures 7.10, 7.11 and 7.12 show the CO_2 emission level, weight and power (respectively) of the average gasoline car sold by a manufacturer in 2014 on the German market. The sales-weighted average values are not perfectly accurate, as these calculations make use of the estimated market we defined in chapter 4. These figures illustrate how the characteristics of the average car

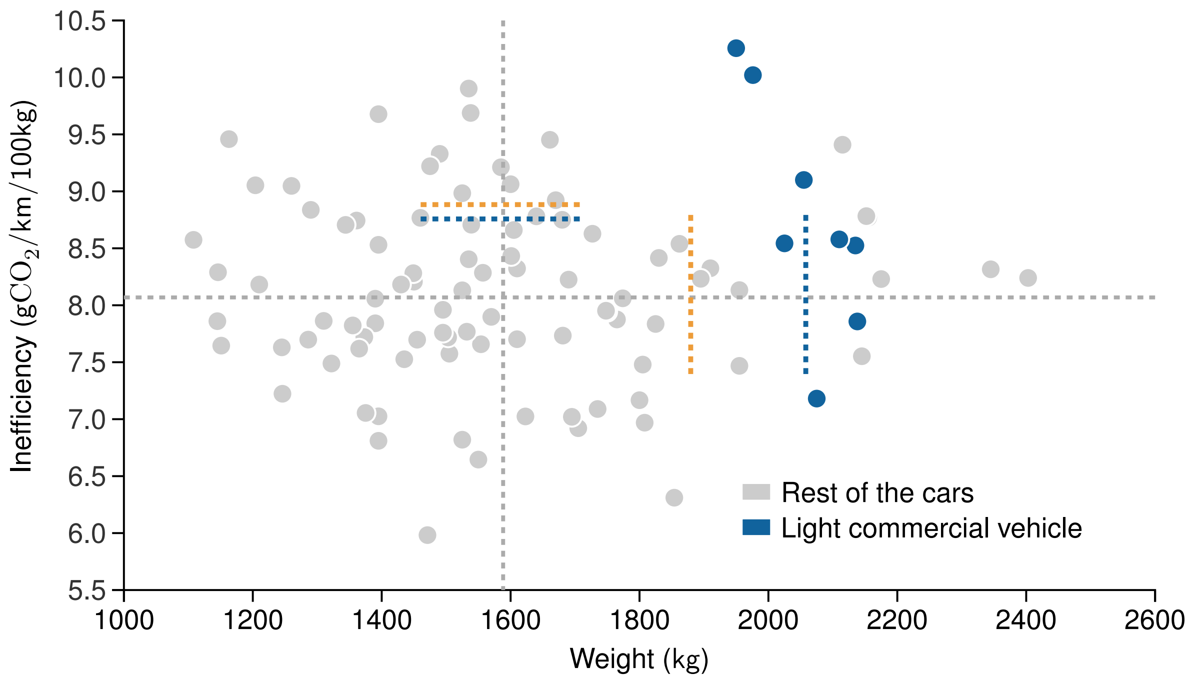

Figure 7.9: Light commercial vehicles have inefficiency higher than the average and weight much higher than the average.
Gray line: $\mu(char)$. Blue line: $\mu_{LCV}(char)$. Orange line: $\sigma(char)$.

sold vary between manufacturers, for the top-12 manufacturers. To quantify this variability, the coefficient of variation c_v is used (see 5.3). The respective figures for inefficiency, surface and width are in appendix C.3. The figures for diesel vehicles are not included in this report, but the numeric results are in table 5.3. We observe in particular that:

- Width is the least varying characteristic among car-makers. They tend to sell gasoline cars that are on average between 1.6 and $1.8\{m\}$ wide, and diesel cars that are on average $1.8\{m\}$ wide, with 3% variation between car makers. Thus a charge indexed on width would affect manufacturers very evenly.
- The surface of the average diesel car also show low variations (3%), while the average gasoline cars have higher variations of their surface (11%).
- Inefficiency shows moderate variations between manufacturers $(12\%$ for gasoline sales, 8% for diesel sales),
- variations are higher for weight $(13\%$ for gasoline sales, 15% for diesel sales),
- and higher for CO_2 emissions $(18\%$ for gasoline sales, 17% for diesel sales).
- By far the largest variations are observed for power $(56\%$ for gasoline sales, 27% for diesel sales), suggesting that a charge indexed on power would affect manufacturers very unevenly, benefiting some and detrimenting others.

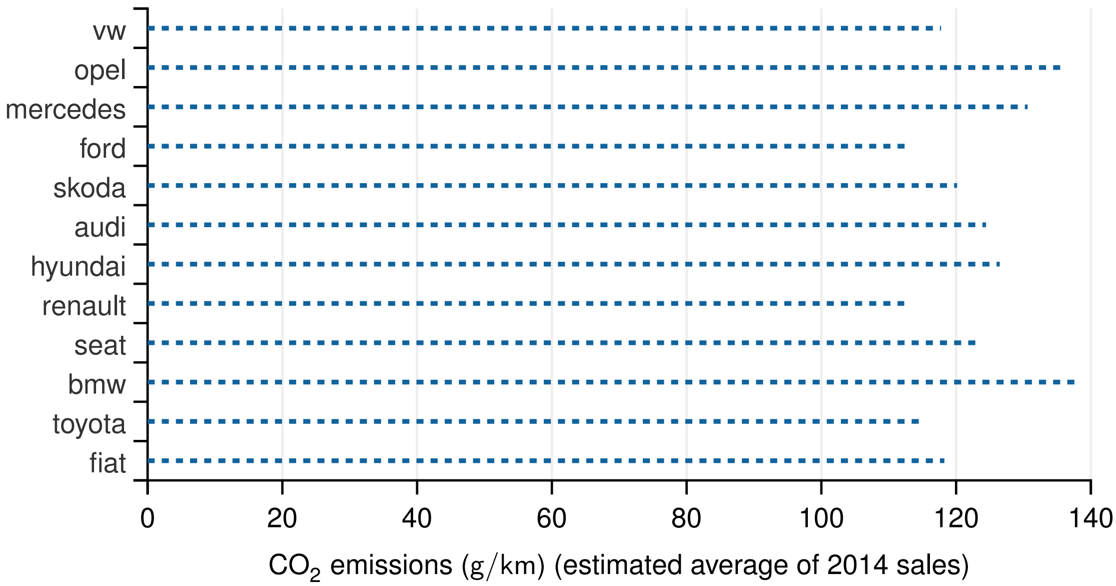

Figure 7.10: Variations of average CO_2 emissions among car-makers, $\mathbf{c_v = 0.18}$.

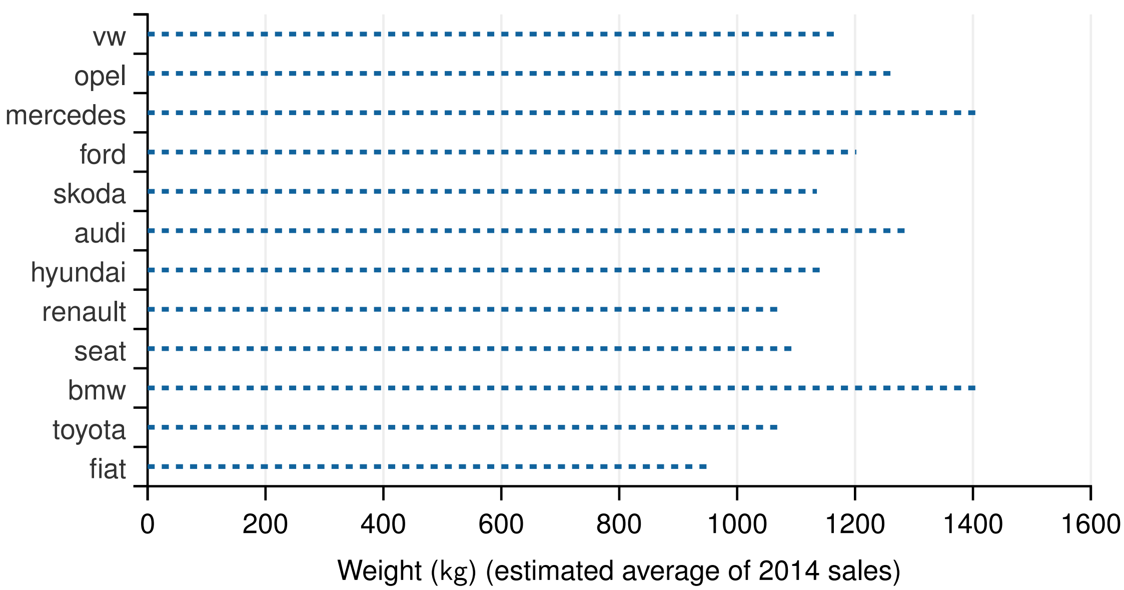

Figure 7.11: Variations of average weight among car-makers, $\mathbf{c_v = 0.13}$

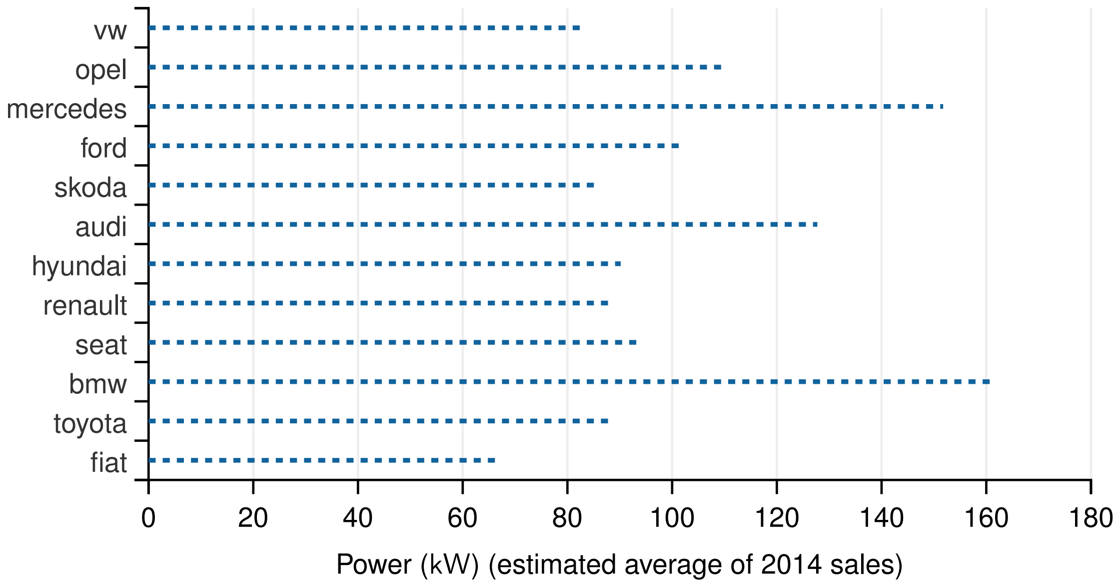

Figure 7.12: Variations of average power among car-makers, $\mathbf{c_v = 0.56}$

Summary

The metrics obtained regarding families, professionals and industrial neutrality are gathered in table 7.6. $dev_{family\,cars}$ and dev_{LCV} should be close to zero (for a vehicle characteristic to be neutral towards families/professionals) or negative (in which case the corresponding policy would benefit families/professionals), but ideally not high positive numbers. c_v should be as close to zero as possible so that all car-makers are impacted evenly. Thus we apply the following color code to these results:

$\mathbf{dev_{family\ cars}}$ $\mathbf{dev_{LCV}}$	$\mathbf{< 0.2}$	$\mathbf{0.2 < < 0.4}$	$\mathbf{0.4 < < 0.6}$	$\mathbf{0.6 < < 0.8}$	$\mathbf{0.8 <}$
COLOR CODE	++	+	o	–	– –
$\mathbf{c}_v$	$\mathbf{0 < < 0.05}$	$\mathbf{0.05 < < 0.1}$	$\mathbf{0.1 < < 0.15}$	$\mathbf{0.15 < < 0.2}$	$\mathbf{0.2 <}$

Aggregations of the metrics for each topic were simply done by giving the same weight to diesel and gasoline cars. The resulting potentials of each vehicle characteristic regarding families, professionals and industrial neutrality are presented in table 7.4.

Gasoline	Power	CO_2	Inefficiency	Weight	Surface	Width
$dev_{family\,cars}$	-0.4	0.6	-0.3	0.7	0.4	0.6
dev_{LCV}	–	–	–	–	–	–
c_v	0.56	0.18	0.12	0.13	0.11	0.03

Diesel	Power	CO_2	Inefficiency	Weight	Surface	Width
$dev_{family\,cars}$	-0.4	0.004	0.1	-0.03	0.004	0.2
dev_{LCV}	-0.1	1.8	0.8	1.6	1.7	1.6
c_v	0.27	0.17	0.08	0.15	0.03	0.03

Table 7.5: Metrics related to families, professionals and industrials

	Power	**CO_2**	**Inefficiency**	**Weight**	**Surface**	**Width**
FAMILIES	++	+	++	+	+	+
PROFESSIONALS	++	– –	– –	– –	– –	– –
INDUSTRIAL NEUTRALITY	– –	–	o	o	+	++

Table 7.6: No vehicle characteristic would put a particular financial burden on family cars. All except power would particularly impact professionals. A car fee indexed on weight or CO_2 emissions would moderately impact some car manufacturers more than others.

7.4 Summary of the potentials

Efficiency is clearly not suited to index a car fee with regard to the objectives we have defined. Efficiency is indeed on average increasing with the size, weight, and price of a car. Thus, charging efficiency would favour the use of larger and heavier cars, and put more financial burden on cheap cars.

The insights gained after analysing the dataset as a whole (chapter 6) are confirmed. Sufficiency characteristics (weight, surface and width) are well correlated to both environmental performance and price. CO_2 emissions by contrast correlate perfectly with environmental performance, but would likely result in less equitable policies if used to index a large-scale urban car fee. This difference can seem insignificant, but it may be a decisive one for politicians willing to introduce an ambitious car fee in their cities, given that acceptance is often considered as the main hurdle to such an endeavour.

For all indexes except power, a special rate would best be applied to professionals so that their heavy and emitting vehicles are not overly charged. Regardless of the index considered, families

	Power	CO_2	Inefficiency	Weight	Surface	Width
ENVIRONMENT	o	++	o	+	o	o
SPACE OCCUPATION	+	o	−−	++	++	++
VERTICAL EQUITY	+	o	−−	+	+	+
EQUITY	++	o	−−	++	+	+
ACCEPTABILITY	+	o	−−	++	+	+
FAMILIES	++	+	++	+	+	+
PROFESSIONALS	++	−−	−−	−−	−−	−−
INDUSTRIAL NEUTRALITY	−−	−	o	o	+	++

Table 7.7: Potentials of the candidate vehicle characteristics regarding the defined objectives

would not be particularly detrimented by the corresponding differentiated car fee. In case a city council is keen on not distorting the competition between car-makers, it would best use surface or width as indexes. Weight, efficiency and CO_2 would moderately distort competition. Indexing a car fee on power would strongly detriment some car manufacturers and benefit others. Industrial neutrality may also appear as a secondary issue, however as illustrated by the resolute opposition of some car-makers to a CO_2-based charge proposed by the city of London a few years ago[1] (BBC 2008), in large cities it may play a role in the successful introduction of an ambitious car policy.

[1]The proposed charge was partially differentiated though, targeting only very polluting and very low-emission vehicles.

Chapter 8

Discussing an effective implementation

8.1 Possible formats

In this section we mention the diversity of the possible formats when implementing a car fee at the city level. This diversity justifies the approach that was adopted to assess possible indexes in terms of potentials independent of any particular format and pricing scheme. In the same time, it illustrates how assessing potentials is at best the first step when designing an actual implementation, and that further consequential decisions have to be made. Discussing these decisions in detail is out of the scope of this work, and would often be done best in the context of a less scientific and more political debate.

Charging in space and time

How could the progressive charge we have mentioned until now be raised? The method should be as simple as possible, while allowing the targeted progessivity. At the national level progressive purchase taxes exist (see 1.2), but it is out of the jurisdiction of a city to introduce a purchase tax on vehicles. Falling within the jurisdiction of a city would be the introduction of a yearly tax on its residents' vehicles. However if commuting vehicles are outweighing residents' vehicles in a city during the day, such a tax make little sense. To our knowledge (the Ecopass in Milan and the failed attempt to charge based on CO_2 in London) a differentiated car fee at the city level can only be implemented through an urban toll.

Urban tolls however can take many forms. They can cover more or less ambitious areas of a city. A charge can be applied for being inside a certain area (like in London) or for crossing a given cordon (like in Stockholm). Time is also a critical variable in the design of congestion charging schemes, in which higher fees are applied during peak hours. Even when an environmental charging scheme was in place in Milan, it had to be paid only between 7:30 a.m. and 7:30 p.m. If a city wants to implement a progressive car charge based on one of the vehicle characteristics discussed in the previous chapter, those choices would have to be made in a similar manner.

Price structures

To illustrate possible price structures, we consider an example in which a city decides to introduce a “feebate” (fee and rebate), increasing linearly with weight, with all cars above a “pivot mass” pm paying a fee, and all cars under receiving a rebate. The feebate is applied daily on all cars entering the city after a system of urban tolls has been installed. The following formula could be used in this case to calculate the feebate applying to each vehicle:

$$f_i = (m_i - pm) * r$$

where:

f_i is the feebate paid (if > 0) or received (if < 0) by car i, in €.

pm is the pivot mass, the mass under which a rebate is received, in kg.

r is the incentive rate, in €$/\text{kg}$.

If it is finally decided that no vehicle will be exempted and that the price will be set to 0 € only for the lightest vehicle on the market, we obtain a fee linearly increasing with the weight and concerning all cars. To calculate its amount it is decided that cars should on average pay 5 € per day. We take this average fee as it is close to the ones used by the cities of Milan and Stockholm for their congestion charging schemes. In London the charges are higher, above 10 € (Papaix and Meurisse 2013). We calculated the fee that would result of these decisions if they were applied to a car market made of our gasoline cars[1]. The incentive rate in this case would be of 1.3 € for every 100kg. As an illustration, the following table gives the amounts that would be charged in this case on the most sold vehicles in six weight categories:

Weight ($*1000\text{kg}$)	< 1	$1 < < 1.2$	$1.2 < < 1.4$	$1.4 < < 1.6$	$1.6 < < 1.8$	$1.8 <$
Model	VW Up	VW Polo	VW Golf	VW Tiguan	Mercedes E	Mercedes S
Fee	0.6€	2.2€	4.2€	8.1€	9.6€	14.1€

If in another city it is decided that the revenues should be the same (5€ per day per vehicle on average), but that the pivot mass should be set 200kg below the average mass so that only particularly light vehicles receive a rebate, it gives an incentive rate of 2.5€ for every 100kg. Taking the same vehicles to illustrate the prices that would be paid, we obtain:

Weight ($*1000\text{kg}$)	< 1	$1 < < 1.2$	$1.2 < < 1.4$	$1.4 < < 1.6$	$1.6 < < 1.8$	$1.8 <$
Model	VW Up	VW Polo	VW Golf	VW Tiguan	Mercedes E	Mercedes S
Feebate	-3.3€	-0.3€	3.6€	11.0€	13.8€	22.3€

[1] We don’t carry the same analysis for diesel vehicles as the results would be similar and do little to show the diversity of possible price structures.

It is easy to see the diversity of schemes that can be considered. We discussed linear increases in our examples, but non-linear increases are also conceivable. Generally speaking, critical variables to decide on a scheme are the revenues derived from it (and thus the average sum paid by drivers), the cars that are concerned, and the rate of increase of the charge. Rationale approaches to make these decisions exist, and mostly consist in pricing externalities, *i.e.* giving a price to costs that are otherwise not accounted for. In the case of transport environmental pricing consists in evaluating the costs of accidents, of diseases due to pollution, *etc.* (Suter and Walter 2001). Another example of an economic approach, in (MIT 2009) the authors propose the introduction of a feebate on the purchase of new vehicles. They choose its amount to compensate for the fact that individuals value the fuel expenses only over the first three years when buying a vehicle, thus underestimating the costs associated with a high-consumption vehicle.

However as noted in (Suter and Walter 2001), "the strong and pure foundation on neoclassical welfare economics of pricing in transport is not uncontested". Following the introduction of the "Heavy Vehicle Fee"[2] in Switzerland, they observe that although initially founded on external environmental costs, the approach used to determine the pricing scheme eventually shifted to a "standard price approach", in which the price is set so that a target reaction is obtained. More generally, they argue that broad political goals should be able to prevail over pure economic thinking when deciding on a price structure.

The correlations and metrics calculated in chapter 7 will remain exactly the same when replacing a vehicle characteristic by a price linearly depending on this vehicle characteristic. For instance the values of a car charge linearly based on weight would correlate to CO_2, price or surface exactly as weight itself. Deviation coefficients and the coefficient of variation among car-makers would also remain constant. Thus, the tables and graphs presented for weight in chapter 7 apply directly to the corresponding linearly increasing charge. If non-linear price structures are chosen, these metrics have to be recalculated, however the qualititative conclusions will likely remain similar.

Exemptions

All cities that have implemented urban tolls have also introduced exemptions and discounts. In London, exemptions concern vehicles transporting disabled persons, low-emission vehicles, vehicles with more than 9 seats and some official vehicles (breakdown and recovery vehicles). Residents are granted a 90% discount, and fleet vehicles a 25% discount. As in London, exemptions exist for categories of clean vehicles in Stockholm and Milan, as well as for some public or emergency vehicles. As we noted in 5.3, if a city decides to index an urban toll on CO_2 emissions or sufficiency, discounts should certainly be applied to professionals using light commercial vehicles, so that they are not overcharged.

Allocation of revenue

Allocating the revenue of a car charge to meaningful goals and announcing it well in advance as an integral part of the scheme certainly eases its introduction (Suter and Walter 2001). For

[2] Charge applied to trucks in Switzerland based on their weight and the distance driven.

instance, the revenue generated by the Swiss Heavy Vehicle Fee (1.5 billion € in 2014), is allocated for $2/3$ to the Swiss Confederation for PuT projects, and for $1/3$ to cantons for road transport costs. In London, £1.2 billion revenue has been generated between 2003 and 2014, of which the vast majority (£960 million) has been invested in the bus network (TfL 2014b). In Milan the more modest revenue is exclusively dedicated to sustainable mobility. In 2012 for example it was allocated to underground and surface PuT, and to extend a bike sharing system (Milano 2013). In the case of a differentiated urban toll, the issues regarding revenue and its allocation would be largely unchanged.

8.2 Feasibility

Technical feasibility

Although urban tolls appear at first sight as rather complex systems, technical feasibility is widely regarded as a non-issue when discussing road charging schemes (Suter and Walter 2001). This feasibility is best illustrated by the fact that tolling infrastructures are successfully operated in Singapore, London, Stockholm and Milan. All these systems rely on cameras to automatically recognise vehicles' plates. The plate number is then compared to a database to obtain further information about a vehicle before a charge is applied. The fact that these systems all require owners of vehicles to register their vehicles and are able to deal with exemptions show that modulating the charge based on a vehicle's characteristic would not imply much overhead. The concerned vehicle's characteristic would simply have to be recorded in the database at the time of registration.

Yet feasible doesn't mean easy. Technical issues that have been observed in the cities where urban tolls were introduced mainly concern the reliability of the plate recognition system. In Stockholm, residents have been erroneously charged because similar plates are in use in other European countries. Issues related to online payments and registration have also arisen in Milan and London.

Revenue

The revenues generated by existing charging schemes show the financial viability of this type of policy. The net revenue to income ratio was less than 50% in London when the congestion charge was introduced. For the year 2014/2015, it has risen to almost 70% (TfL 2015). However some authors have pointed out the particularly high collection costs in London compared to Stockholm, where approximately the same number of vehicle is charged but costs are 10 times lower (Jansson 2010). This large difference is attributed to the design of the plate recognition system. In Stockholm, only 18 gates equipped with cameras are enough to control all vehicles crossing the cordons. In London the topology of the city makes the use of gates more complicated, and plate recognition happens within the charging area, in a more complex manner. Still, all congestion charging schemes generate revenue. In Milan and Stockholm, where the charges are lower than in London and plates are recognised by gates[3], revenue to income ratios are around 50% and

[3] 43 gates in Milan.

70% respectively (Papaix and Meurisse 2013).

Abandoned Ecopass in Milan

The fact that the pollution charging scheme introduced in Milan from 2008 was replaced in 2012 by a more conventional congestion charging is of particular interest for our discussion. When charging all cars entering a certain area regardless of their characteristics, the financial incentive put on drivers is constant with time and perfectly known. The generated revenue only varies with the number of cars entering the charged area daily and is thus well predictable. On the other hand, when modulating a charge based on each vehicle's characteristics, the financial incentive put on drivers will depend on the car they use, and the generated revenue will depend on the fleet of vehicles entering the charged area and their characteristics. Thus if following the introduction of a progressive scheme drivers rapidly change their cars to pay less or nothing, both the incentives put on drivers and the revenues of the charging scheme are reduced, threatening its effectiveness and its financial viability. This has happened in Milan[4] (Milano 2008) and may have contributed to the city shifting to a congestion charge.

A simple solution to this problem is to adapt the price structure every year to keep a constant pressure on drivers and constant revenues, as in the case of a purchase rebate (MIT 2009). This couldn't be done easily in Milan because emission standard, the characteristic used to modulate the charge, is a discrete variable with only six categories (Euro-1 to 6), and almost all vehicles sold since 2001 in Europe fall into only four categories (Euro-3 to 6) (Peter Mock 2013). If many drivers have bought Euro 5-compliant vehicles after the introduction of the Ecopass, it could have been decided to charge all Euro-5 vehicles and exempt only Euro-6 vehicles, but we see this vehicle characteristic offers very little progressivity compared to the ones we have considered in this work.

8.3 Impacts

Environment and congestion

It is difficult to predict what would be the impact of the policies we consider in this work, as they have never been implemented. However looking at the results obtained by the congestion charges already mentioned certainly gives an idea of the order of magnitude of the achievable results. In Milan, Stockholm and London, traffic volumes have been reduced by 10% to 20% in the restricted area following the introduction of a charging scheme. Injuries have been reduced by 2% to 20%, and NO_x, PM_{10} and CO_2 emissions by 10% to 20%. A progressive charge based on an vehicle characteristic targeting well CO_2 emissions should achieve even better results regarding the environment.

[4] However the characteristic used to modulate the Ecopass (a vehicle's emission standard) has allowed some Milanese to buy brand new SUVs to escape the charge, showing the importance of choosing the modulating characteristic well.

Safety

Discussions regarding safety may arise if a city introduces a charge aimed at decreasing the average weight or size of vehicles. In urban environments, the majority of traffic fatalities occur for pedestrians, bicycles and two-wheelers, especially in emerging markets where mixed use of roads is common (Cahill, Taylor, and Dan Sperling 2013). It is worth stressing that these fatalities, as well as the ones occurring when two vehicles are crashing, are primarily depending on the speed of the vehicle(s), not its size or weight. This being said, occupants of heavier vehicles are safer, at the expense of occupants of lighter vehicles or pedestrians. Overall, large vehicles have a safety disadvantage (Cahill, Taylor, and Dan Sperling 2013). Some authors have investigated economic policies to mitigate the “arms race” in vehicle size, resulting from consumers’ choices of vehicle size that are privately optimal but not socially optimal (Kinler and Wagner 2014).

Rebound effect

Generally speaking, it can be feared that a policy fostering the use of cleaner technologies will *in fine* foster a greater use of these technologies. Depending on the strength of this so-called rebound effect, the impact of a policy can be lessened, reduced to zero, or worse the policy could backfire. A large literature is dedicated to quantify this rebound effect in the case of private cars (Sorrell, Dimitropoulos, and Sommerville 2009). Overall, they show that the long-term rebound effect related to the use of cars consuming less is between 10% and 30%. Thus, the savings expected from a policy fostering the use of greener cars should not be offset by more than $1/3$ by the rebound effect. Moreover the policies we discuss in this work are charges on the usage of a car. Usage charges are precisely the kind of policies that are proposed by some to mitigate the rebound effect following the introduction of an environmental feebate on the purchase of a car (Meurisse 2015).

Car markets in emerging countries

Bearing in mind the distinction between sufficiency and efficiency when designing car policies could be particularly useful in the urban contexts of the emerging countries. As we have seen in chapter 2, problems related to the use of space are particularly acute in emerging cities and stringent measures restricting the use of cars have already been adopted in some. In (Cahill, Taylor, and Dan Sperling 2013), the authors underline the large difference between car markets in developed and emerging countries. In Asia, two-thirds of the vehicles are two- or three-wheelers. Car regulations modeled on the ones exisitng in developed markets may be inadequate, and they advocate for new regulations allowing the introduction of low-mass urban microcars on these markets. More generally, targeting the mass and size of vehicles may be especially adequate and effective in emerging markets.

Synergies with other transport policies

A city charging its cars raises a revenue that is mostly dedicated to public transport (8.2), thus improving the level of service of public transport infrastructures. Moreover, drivers receive a financial incentive to shift to PuT. Following the introduction of a road charging scheme, a 7% increase in surface PuT trips has been observed in Milan, a 4,5% increase in Stockholm, and a 30% increase in London (Papaix and Meurisse 2013).

A progressive charge that would make smaller or lighter vehicles more attractive would also boost the market share and development of electric vehicles. Electric vehicles are indeed especially light on average, in order to counterbalance the low energy density of their batteries and achieve reasonable ranges. Hence, promoting smaller or lighter vehicles is also promoting electric vehicles.

Finally, a tolling system applying a charge adjustable to various car characteristics would be a highly flexible tool for cities, whose usage could easily be adapted to diverse political goals. Among the many use case that are imaginable, a city could decide to charge vehicles based on their width, and announce that in 10 years only narrow vehicles would be allowed in the city. Regained portions of the road would be dedicated to buses and bikes. To allow for a smooth transition and give time and incentives to drivers for buying narrower vehicles, the charge on width would be progressively increased during the 10 years period.

Conclusion

The main contribution of this work is to show that weight as a high and currently unexploited potential for dealing with cars in an urban context. Cities mostly develop policies that place all cars on an equal footing, regardless of their size, emissions, or price. As a result, these policies have low acceptance and limited impact. Congestion charging is an example of such a non-progressive car policy. We considered various vehicle characteristics that could be used to index a differentiated fee on cars at the city level. Weight appears as the most promising one, and more generally we show that policy makers in an urban context may develop promising policies if they target not only efficiency or CO_2 emissions but also sufficiency. A road charge indexed on weight has the potential to foster the use of small and low-emission cars, without distorting much the competition between car-makers. Importantly, this fee also has the potential to be more equitable, and thus better accepted, than a similar one indexed on CO_2[5]. Once implemented, such a charge may give a lot of flexibility to cities for dealing with their cars, and have positive synergies with many other transport policies.

Chapter 8 has shown the numerous topics that can be further discussed or analysed to investigate the effective implementation of a progressive road charge in an urban context. Regarding the specific work we have carried out, *i.e.* assessing the potentials of various vehicle characteristics for modulating a car charge, we consider that it could be extended in two main directions. First, a similar assessment could be made on different datasets, concerning car markets in other countries, without the approximations we have made regarding each model and its numerous versions, and including pollution records. This would give a broader validity to the correlations we found in this work. Then, the metrics we presented in chapter 5 may be refined and new ones introduced to compare other potentials that we haven't explored.

[5] and much more equitable than a fee not indexed on any car characteristic, *e.g.* congestion charging.

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Appendix A

On the consumption of vehicles

A.1 Relative importance of the 3 resistances to motion at different speeds

As we have seen in equation (3.7), the sufficiency of a vehicle chiefly depends on three resistances to motion. These resistances in turn only depend on:

- a few characteristics of the vehicle (its mass m, its friction coefficient C_r, and its aerodynamic coefficients C_x and S),
- the state of motion of the vehicle (speed and acceleration).

To understand these dependencies better, we can first consider a given vehicle with fixed characteristics, and see how the resistances to motion typically change under various circumstances. Figure A.1 presents the relative contributions of the three resistances for typical driving conditions in the city, on the highway and overall. As we can see, the aerodynamic drag is the most important resistance on the highway, while in the city inertia is the strongest hurdle to motion.

Rolling resistance and inertia are both proportional to the weight of the vehicle (equations 3.2 and 3.3). As these forces account for 90% of the fuel consumption in a city context, and 60% on a highway (figure A.1), consumption is logically well-related to weight, especially in an urban context.

A.2 Contribution of the weight to consumption on the NEDC

Here we apply the simple physical model presented in 3.2 to a reference driving cycle, and derive a coefficient linking the level of consumption to the weight of a typical European car. This coefficient obtained using a physical model is compared to the ones obtained with a statistical approach, as a way to validate the simple physical model and its assumptions.

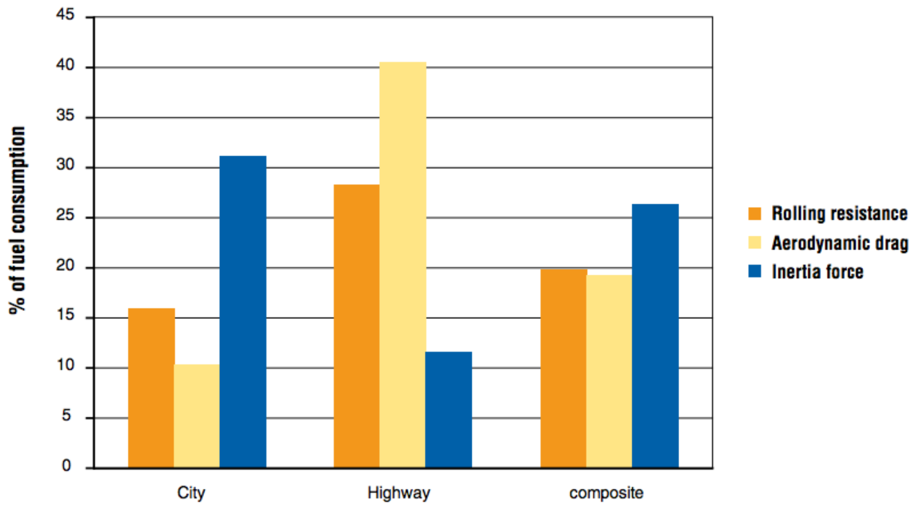

Figure A.1: Influence of driving conditions on aerodynamic drag, rolling resistance and inertia contributions to fuel consumption. Source: (Nemry et al. 2008)

The New European Driving Cycle

The NEDC is the reference cycle for measuring car consumptions in Europe. Is is composed of two subcycles, the Urban Driving Cycle (UDC) and the Extra-Urban Driving Cycle (EUDC). The UDC is repeated four times, before one EUDC takes place. This structure is illustrated on Figure A.2, which shows the speed profile followed by a car during the NEDC.

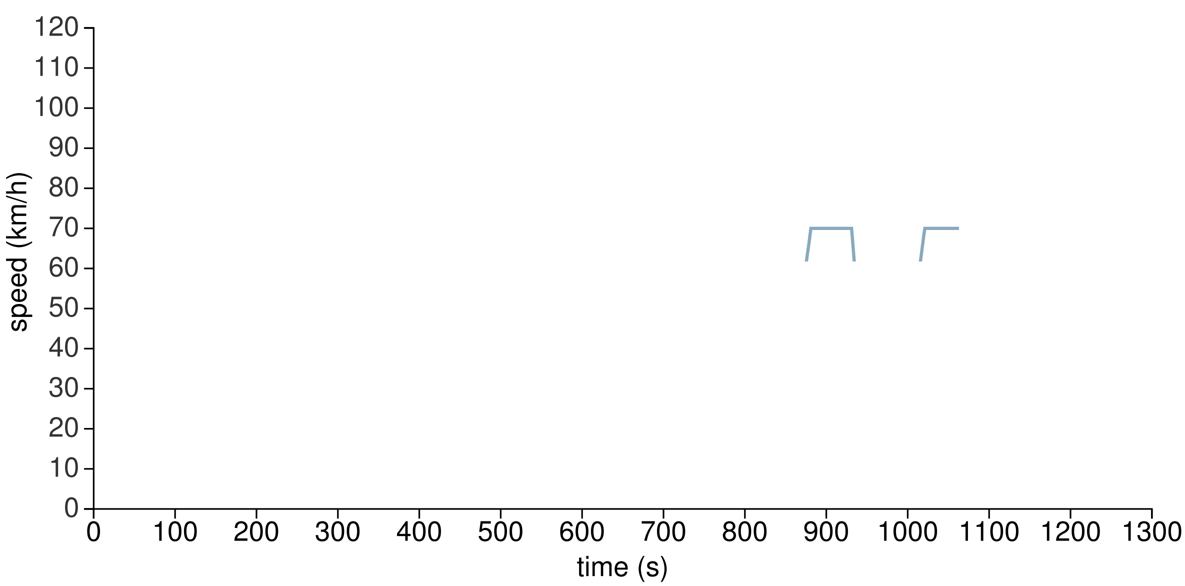

Figure A.2: We use the NEDC as the speed profile $v(t)$ for our calculations.

The NEDC is criticized for systematically underestimating the real-world consumption levels of cars. It will soon be replaced at the European level by a new and more representative test. However in the data we gathered, consumption levels are the official European ones, obtained with the NEDC. Thus we use this cycle for our calculations.

Linear relation between weight and consumption as given by a simple physical approach

Following equations (3.9), (3.7), (3.6), (3.5) and (3.4), it is possible to rewrite E_{tot} as follows:

$$E_{tot} = \int_0^T \underbrace{\frac{1}{\gamma(t)}}_{efficiency} \left(\underbrace{\frac{1}{2}\,\rho\, S\, C_x\, \left(v(t)^3\right)_{acc}}_{air\ resistance} + \underbrace{C_r\, m\, g\, \left(v(t)\right)_{acc}}_{rolling\ resistance} + \underbrace{m\, \left(v(t)\,\frac{dv}{dt}(t)\right)_{acc}}_{inertia} \right) dt \quad [\text{J}] \tag{A.1}$$

It is also possible to decompose this equation in terms that are related to vehicle characteristics on the one hand, and terms related to speed and acceleration during the trip on the other hand:

$$E_{tot} = \frac{1}{2}\rho\, \underbrace{SC_x}_{vehicle} \int_0^T \underbrace{\frac{1}{\gamma(t)}}_{vehicle} \underbrace{\left(v(t)^3\right)_{acc}}_{trip} dt + \underbrace{C_r m}_{vehicle}\, g \int_0^T \underbrace{\frac{1}{\gamma(t)}}_{vehicle} \underbrace{\left(v(t)\right)_{acc}}_{trip} dt + \underbrace{m}_{vehicle} \int_0^T \underbrace{\frac{1}{\gamma(t)}}_{vehicle} \underbrace{\left(v(t)\frac{dv}{dt}(t)\right)_{acc}}_{trip} dt [\text{J}]$$

In 7.1, we conduct a linear regression of consumption against weight, thus obtaining a formula having the following form:

$$C = A\, m + B \qquad [\text{J m}^{-1}] \tag{A.2}$$

Given equations (A.1) and (3.10), and assuming that γ is constant, we obtain

$$A = \frac{1}{\int_0^T v(t)\, dt}\, \frac{1}{\gamma} \left(C_r g \int_0^T \left(v(t)\right)_{acc}\, dt + \int_0^T \left(v(t)\, \frac{dv}{dt}(t) \right)_{acc} dt \right) \qquad [\text{J m}^{-1}\, \text{kg}^{-1}] \tag{A.3}$$

To obtain a first-order approximation of A, we need to replace all the terms in equation (A.3). Conversion of the units from $[\text{J m}^{-1}\, \text{kg}^{-1}]$ to $[\text{L}/100\text{km}\ /100\text{kg}]$ is made using the following conversion factors: $1\,\text{L}/100\text{km} = 10\,\text{kWh}$, and $1\,\text{Wh} = 3600\,\text{J}$.

Trip-related data, *i.e.* speed and acceleration profiles, are taken from the NEDC. Indeed, the consumption figures present in the dataset are the official ones used in Europe, obtained by testing the car on the cycles presented in appendix A.2. As there are three types of cycles (urban, extra-urban and combined), we will obtain three values for A.

Concerning the vehicle characteristics, we make the simplifying assumption that the efficiency $\gamma(t)$ is constant with time. On average, γ is around 0.3. For rolling and aerodynamic coefficients, we use typical values for European cars as reported by (Fontaras and Samaras 2010):

$$\begin{aligned} S &= 2.5\,\text{m}^2 \\ C_x &= 0.3 \\ C_r &= 10\,\text{kg/t} \end{aligned}$$

Finally we obtain three values for A, one for each driving condition. These values are presented in table A.1. The results suggest that the simple physical model we use to stress the difference between sufficiency and efficiency is not perfectly accurate (as expected) but represents well the big picture. In the statistical as well as in the physical approach, the weight plays a greater role in an urban context, which only confirms what was said above. In the city, increasing the weight of a vehicle by 100kg leads on average to an additional consumption of $0.4\text{L}/100\text{km}$.

$\mathbf{A}[\text{L}/100\text{km}\ /100\text{kg}]$	Simple physical model	Gasoline regression	Diesel regression
Urban	0.35	0.47	0.37
Extra-urban	0.23	0.23	0.28
Combined	0.27	0.32	0.31

Table A.1: Linear coefficients between consumption and weight, as predicted by a simple physical model and linear regressions on our dataset.

Appendix B

Further information related to the data

B.1 Models making up for the cheapest decile of 2014 sales

Figure B.1: Gasoline cars belonging to the cheapest decile in our estimated 2014 market, and their price

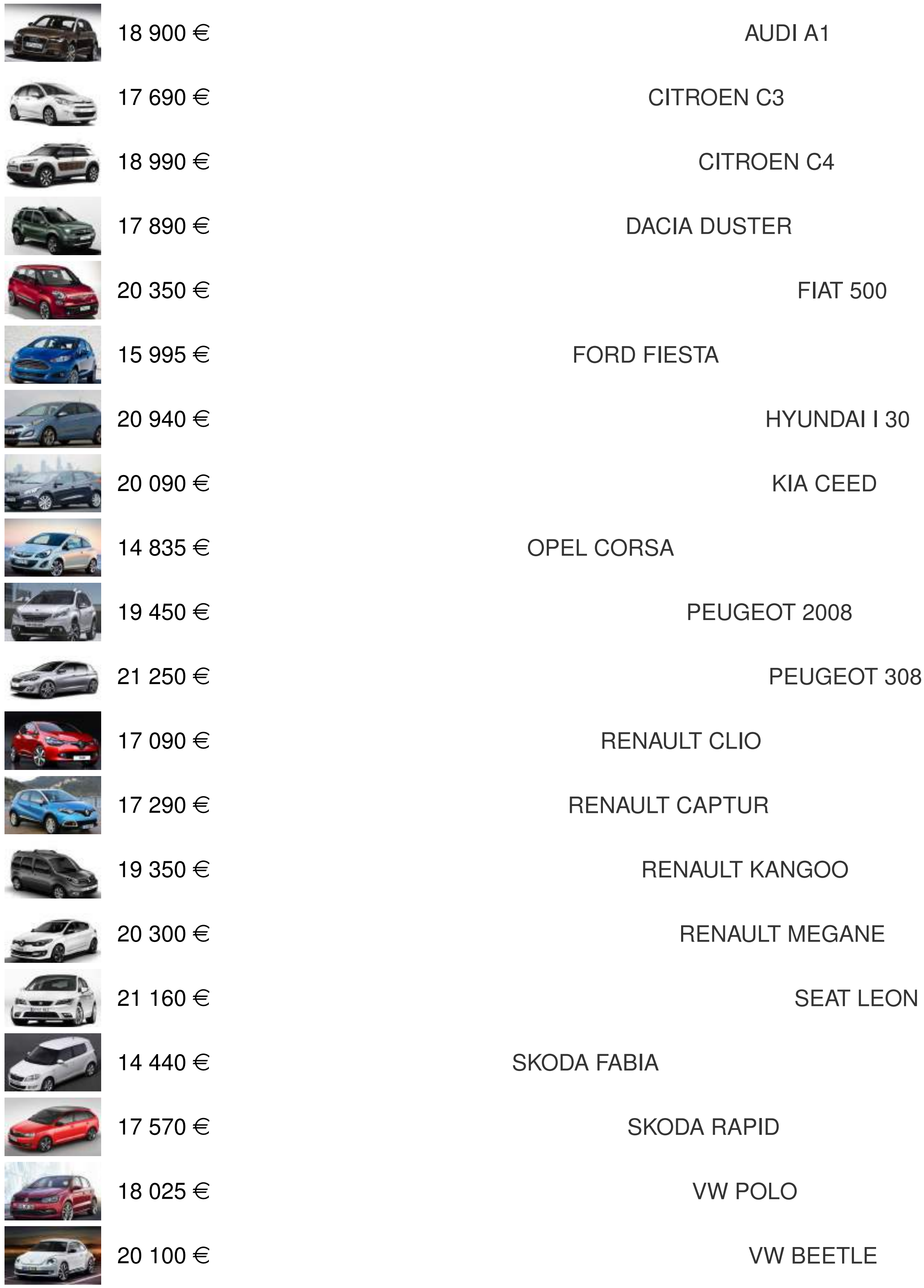

Figure B.2: Diesel cars belonging to the cheapest decile in our estimated 2014 market, and their price

B.2 Family models

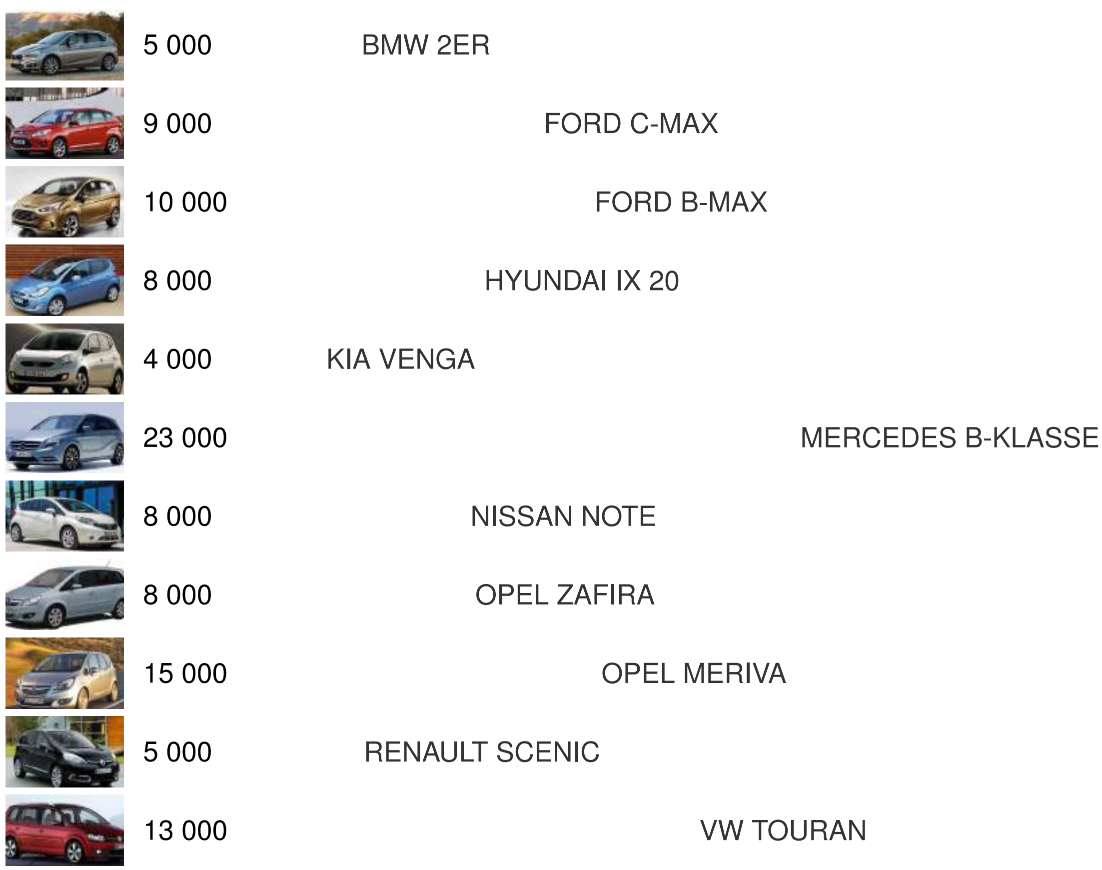

Figure B.3: Gasoline family cars in our estimated 2014 market, and their sales

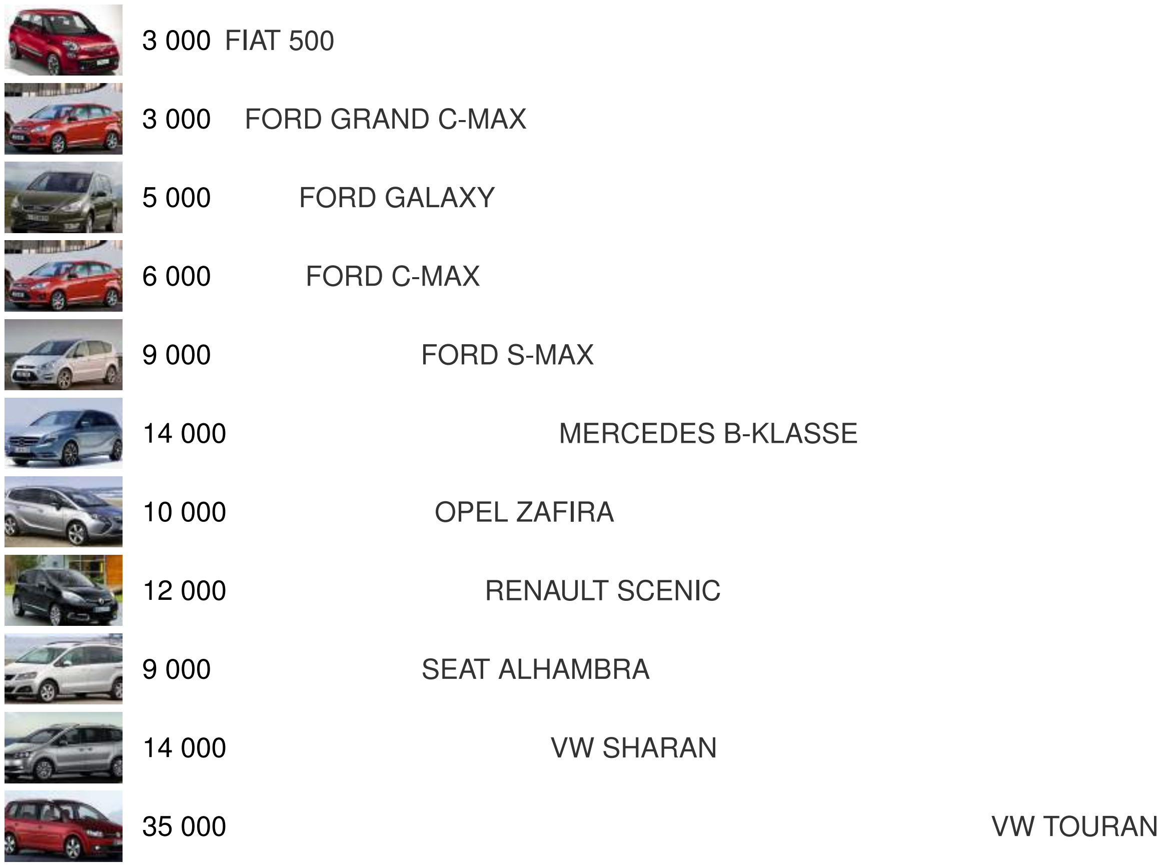

Figure B.4: Diesel family cars in our estimated 2014 market, and their sales

B.3 Light commercial vehicles

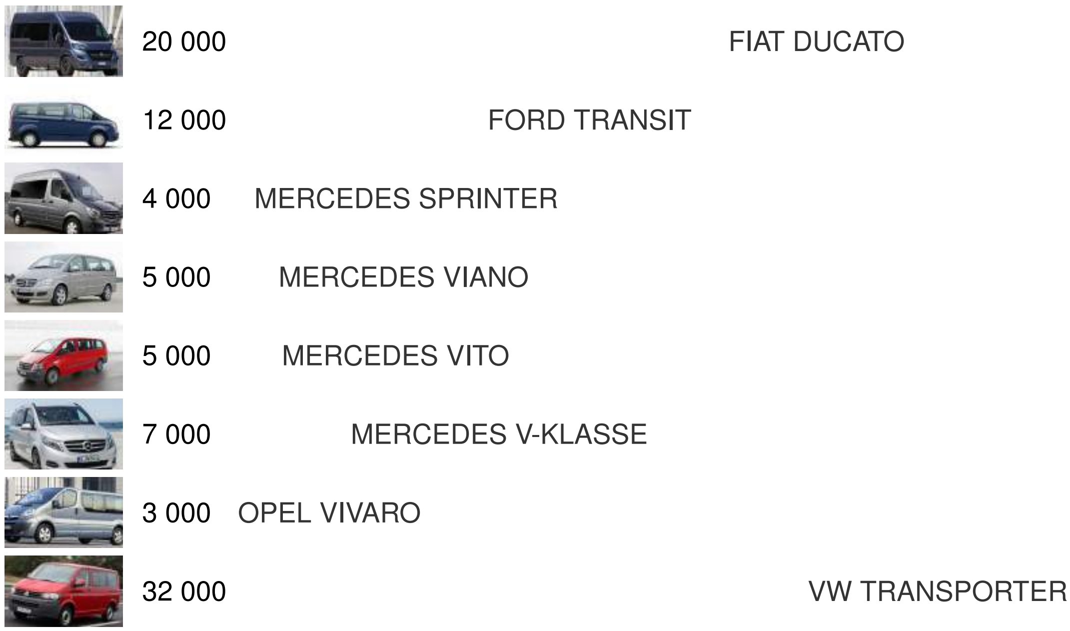

Figure B.5: Light commercial vehicles in our estimated 2014 market, and their sales

Appendix C

Figures not included in the main report

C.1 Environment and space occupation

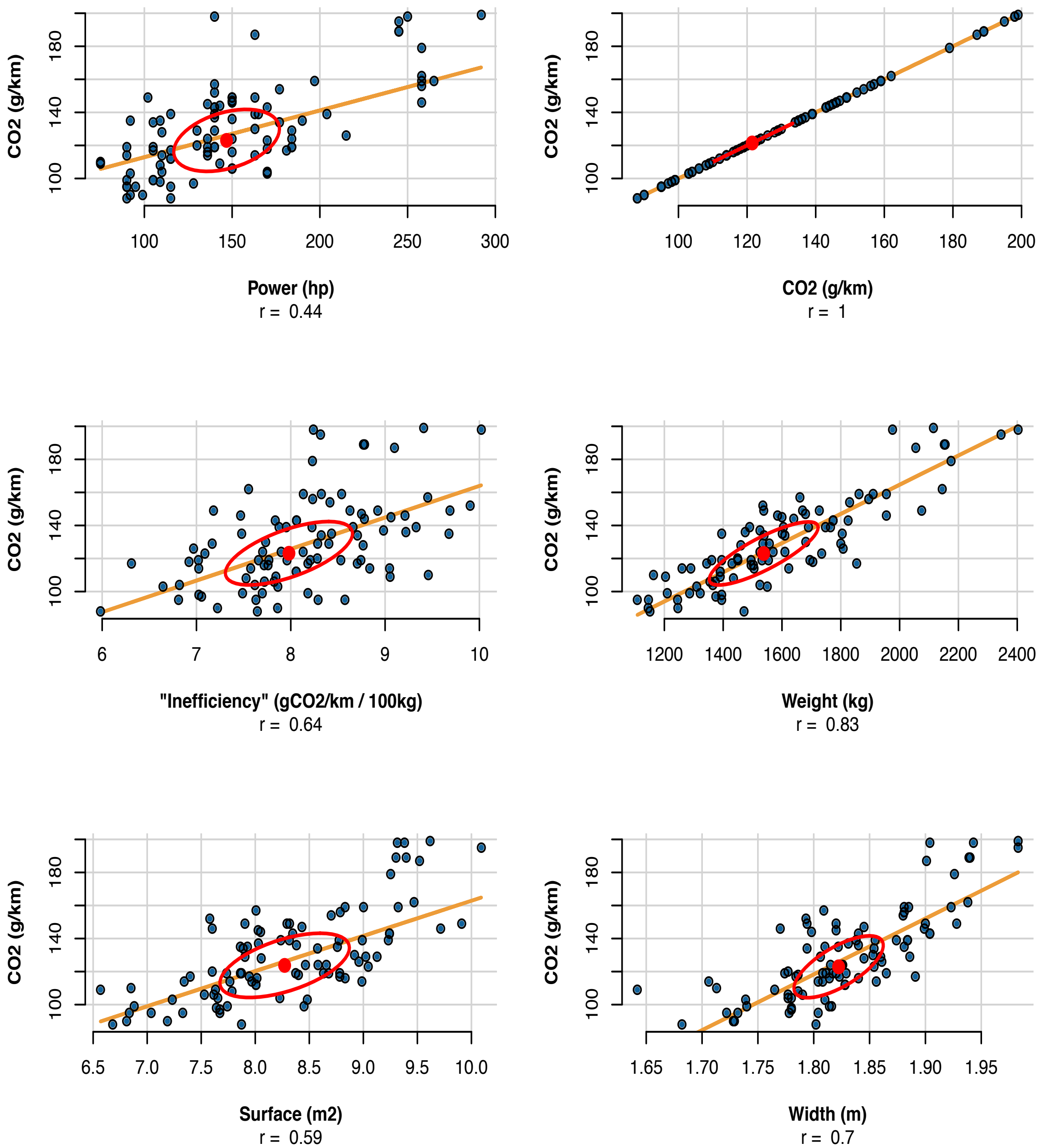

Figure C.1: Potential of the vehicle characteristics for targeting $\mathbf{CO_2}$ - Diesel cars

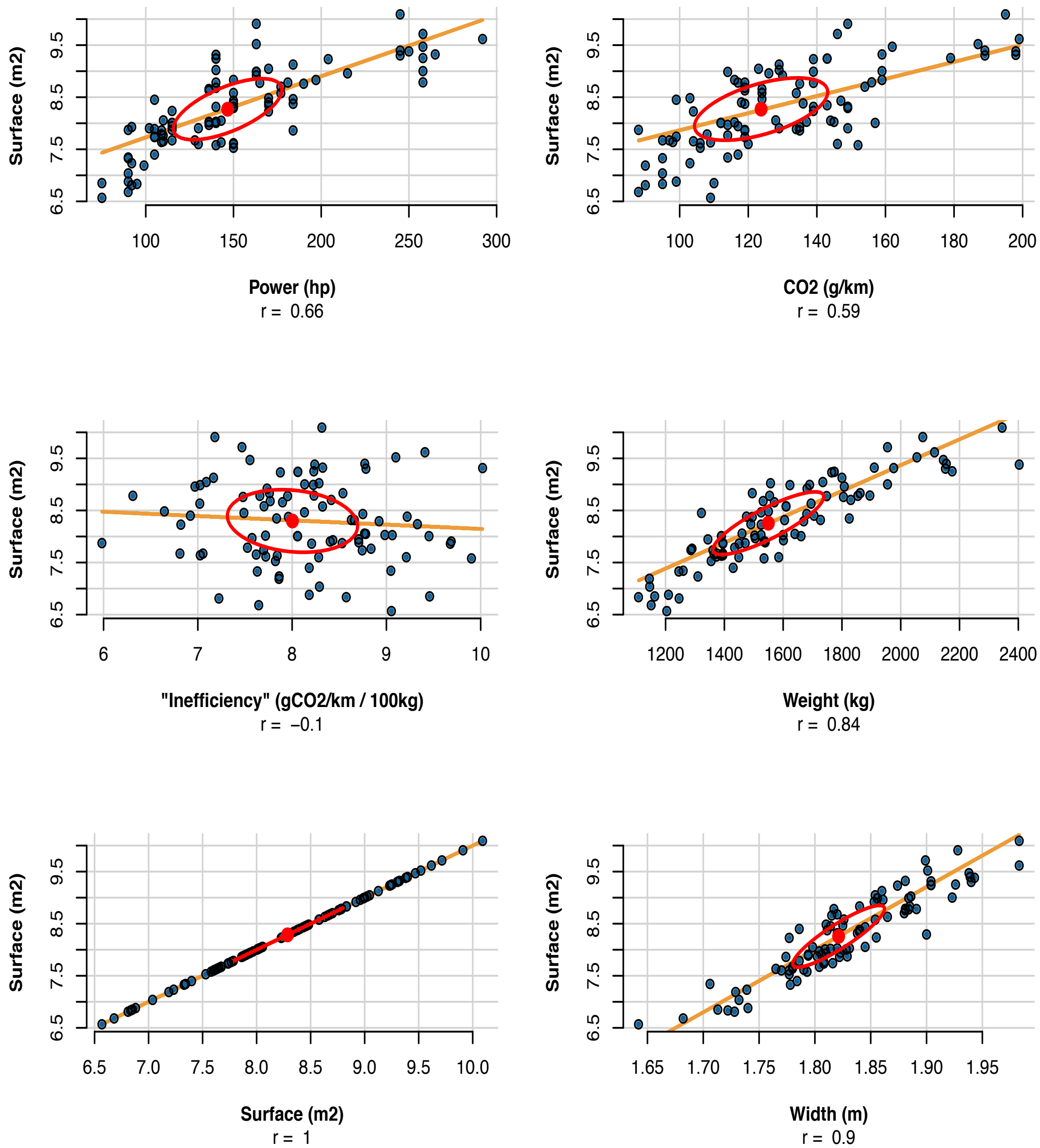

Figure C.2: Potential of the vehicle characteristics for targeting **surface** - Diesel cars

C.2 Equity and acceptability

Vertical equity

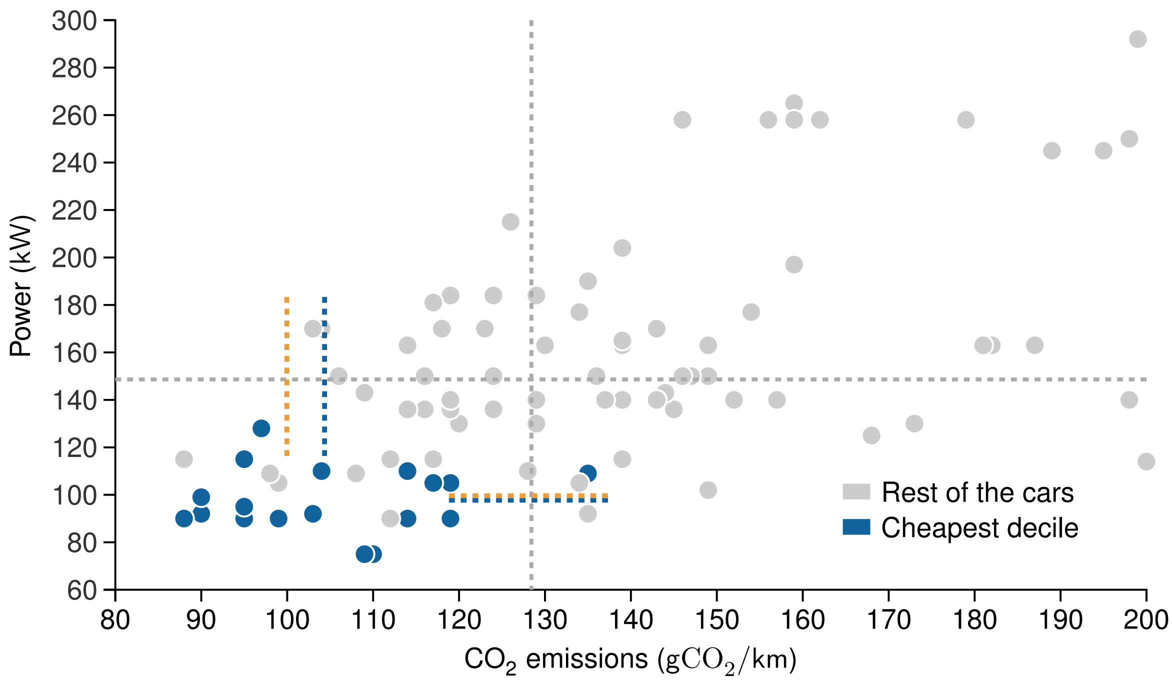

Figure C.3: The cheapest diesel cars have low average emissions and power.
Gray line: $\mu(char)$. Blue line: $\mu_{10\%\,cheapest}(char)$. Orange line: $\sigma(char)$.

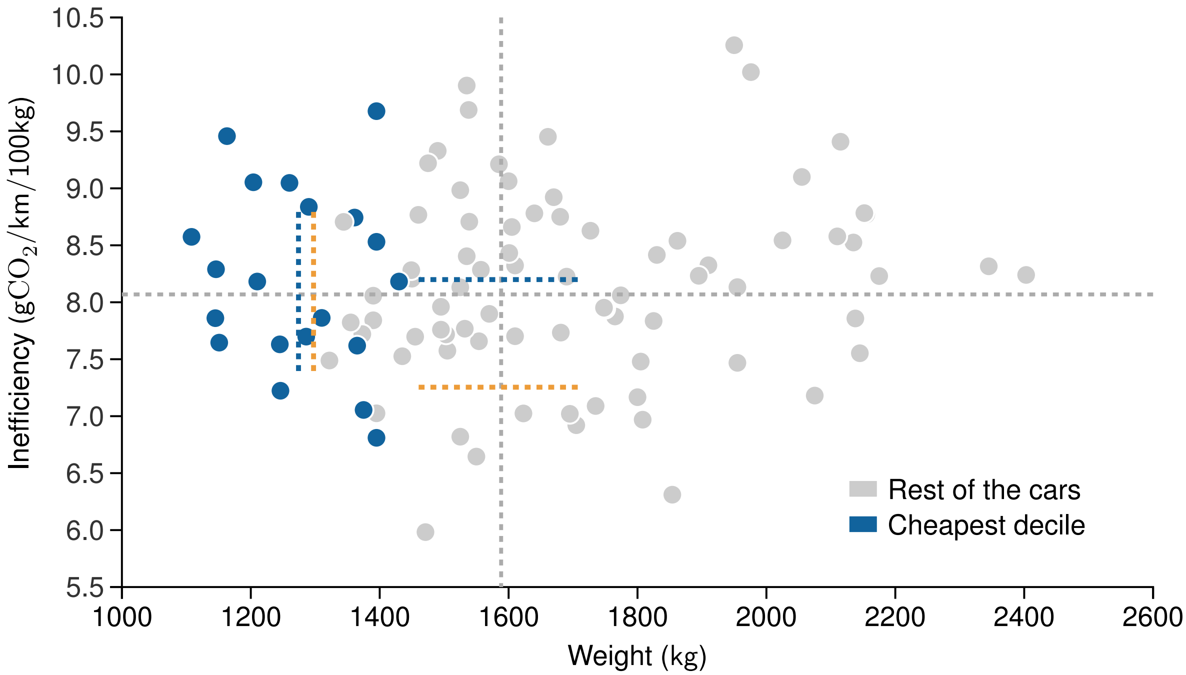

Figure C.4: The cheapest diesel cars have low average weight and average inefficiency. Gray line: $\mu(char)$. Blue line: $\mu_{10\%\,cheapest}(char)$. Orange line: $\sigma(char)$.

Equity

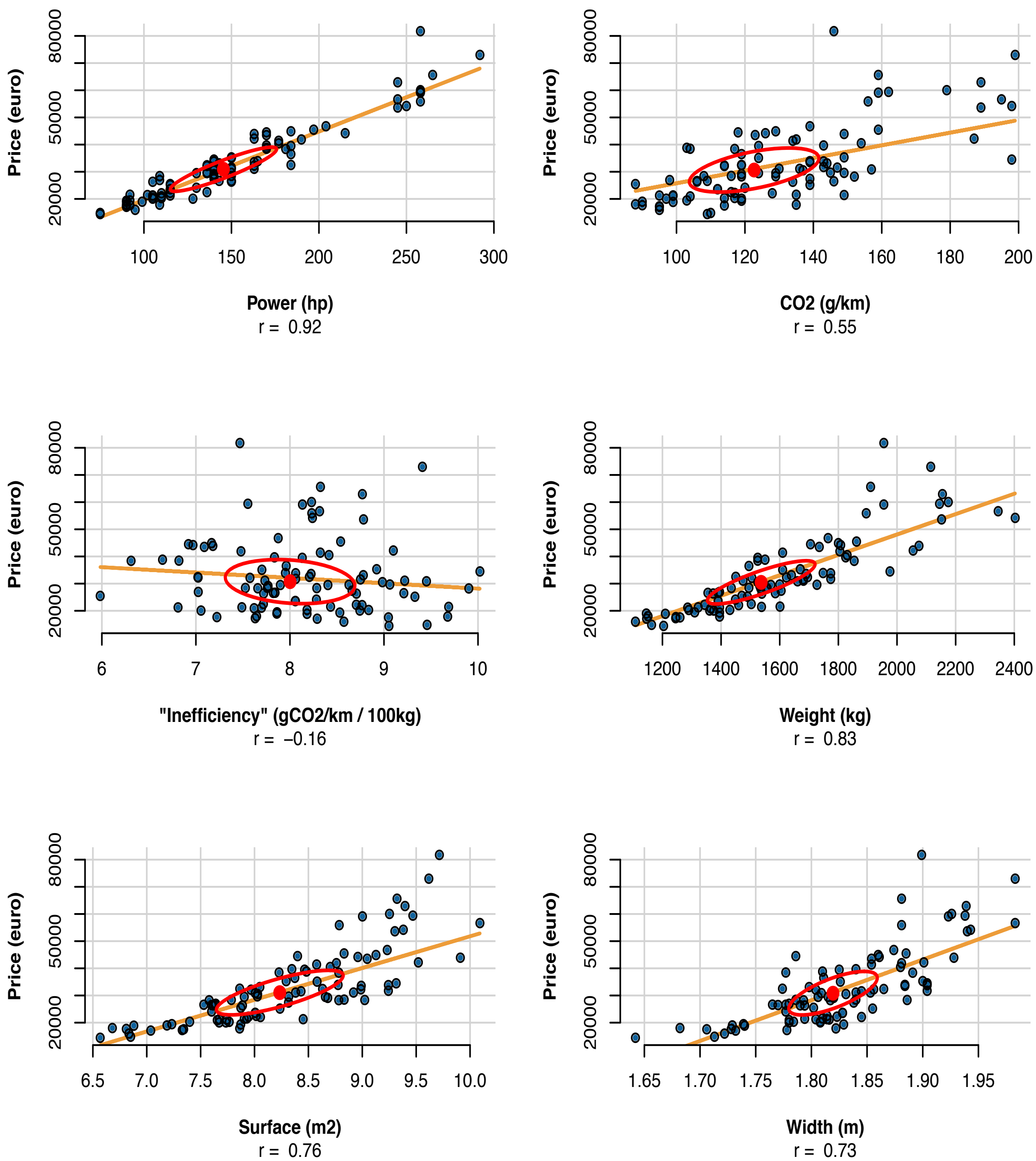

Figure C.5: Potential of the vehicle characteristics for targeting **price** - Diesel cars

C.3 Families, professionals and industrial neutrality

Families

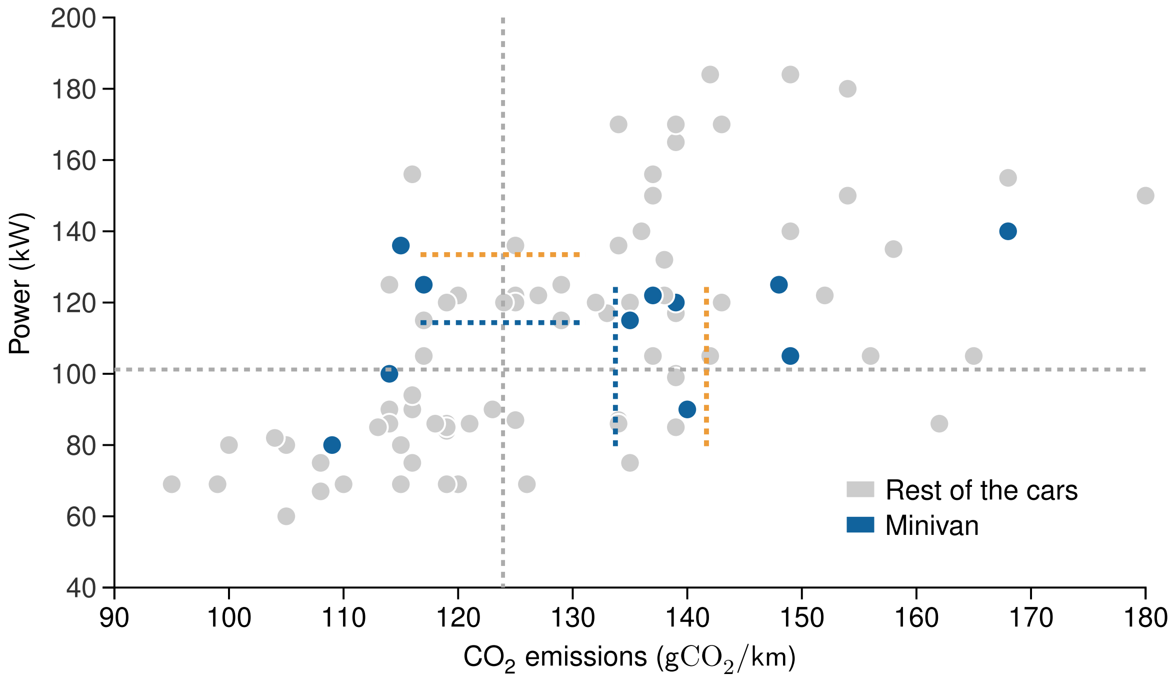

Figure C.6: Gasoline family cars have average CO_2 emissions and power higher than the average.
Gray line: $\mu(char)$. Blue line: $\mu_{family\,cars}(char)$. Orange line: $\sigma(char)$.

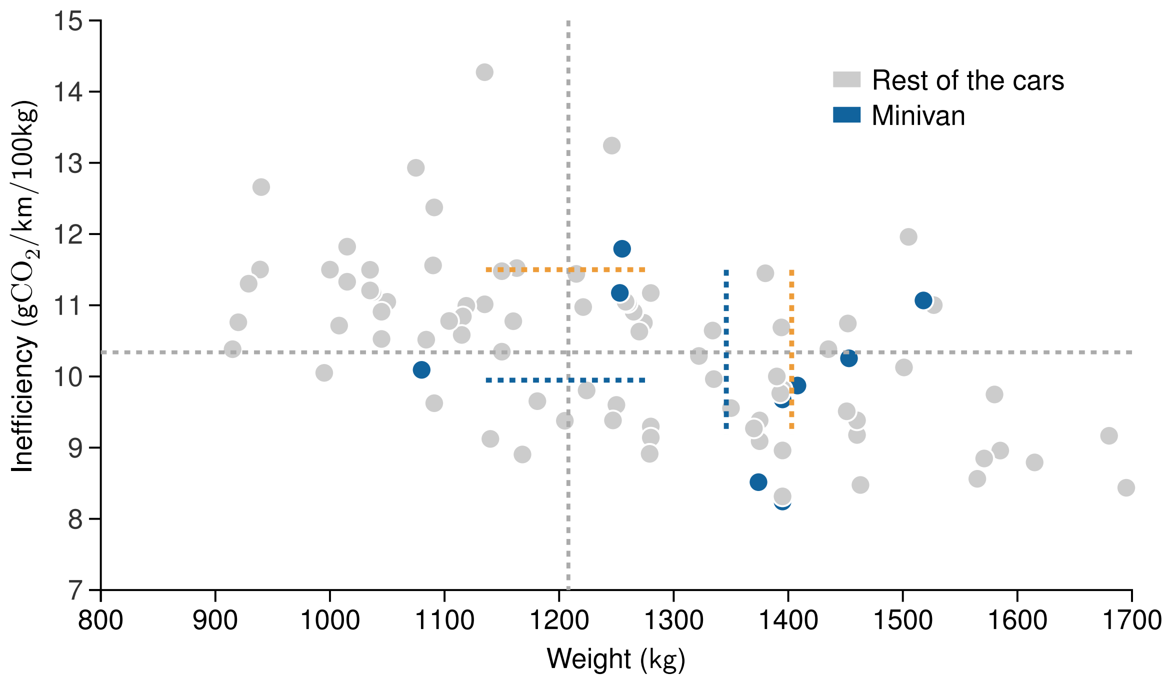

Figure C.7: Gasoline family cars have average inefficiency and weight higher than the average. Gray line: $\mu(char)$. Blue line: $\mu_{family\,cars}(char)$. Orange line: $\sigma(char)$.

Industrial neutrality

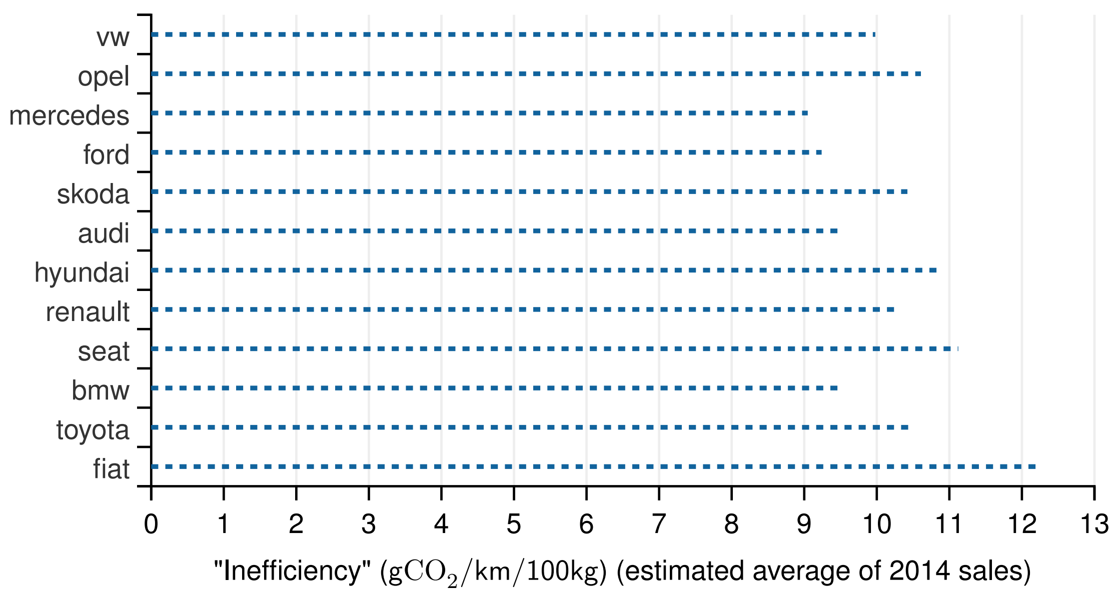

Figure C.8: Variations of average inefficiency among car-makers, $\mathbf{c_v = 0.12}$

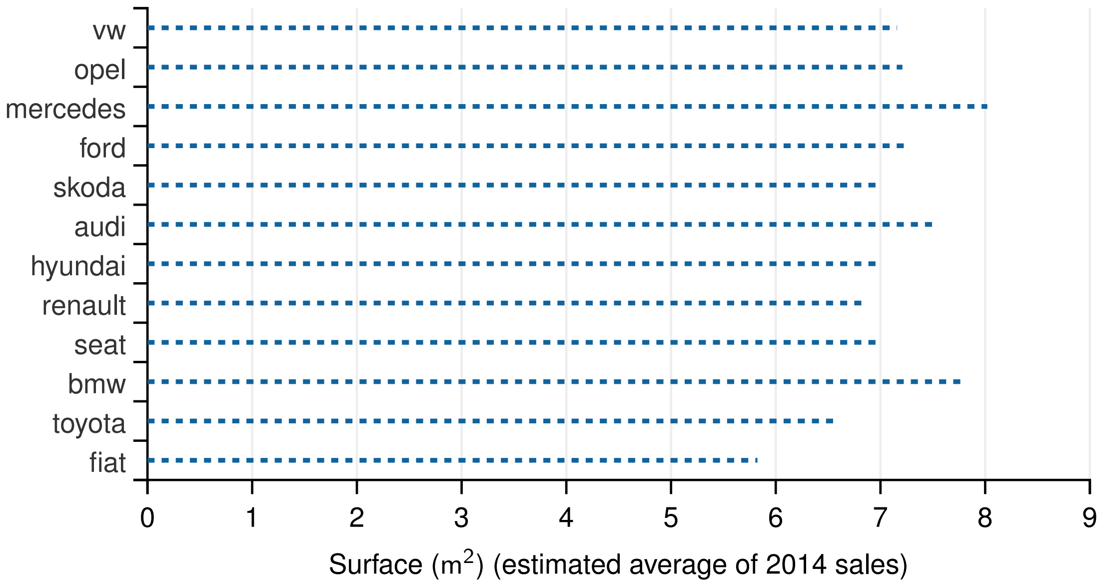

Figure C.9: Variations of average surface among car-makers, $\mathbf{c_v = 0.11}$

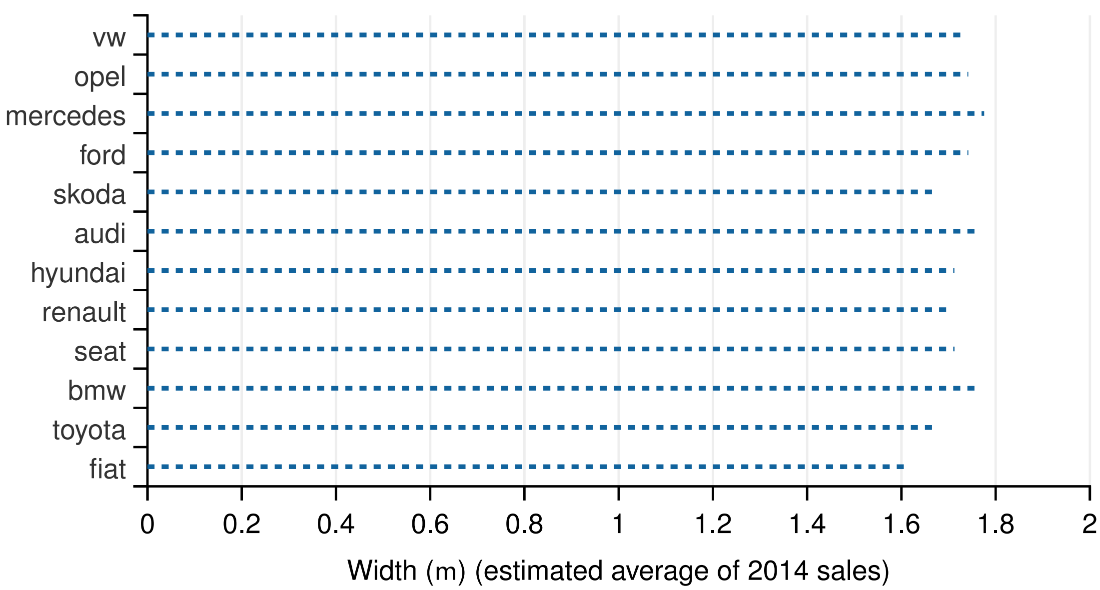

Figure C.10: Variations of average width among car-makers, $\mathbf{c_v = 0.03}$